Essays into Firms, Innovation and Productivity

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Declaration

This thesis is the result of my own work and includes nothing which is the outcome of work done in collaboration except as declared in the Preface and specified in the text. It is not substantially the same as any that I have submitted, or, is being concurrently submitted for a degree or diploma or other qualification at the University of Cambridge or any other University or similar institution except as declared in the Preface and specified in the text. I further state that no substantial part of my thesis has already been submitted, or, is being concurrently submitted for any such degree, diploma or other qualification at the University of Cambridge or any other University or similar institution except as declared in the Preface and specified in the text. It does not exceed the prescribed word limit for the relevant Degree Committee.

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Abstract

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This empirical research aims to understand firm-level innovation and productivity in the context of firm's innovative activities or international activities such as offshoring and exporting. The PhD dissertation consists of three chapters that use the Survery of Business Activities annually provided by the Statistics Korea to gain insights into the link between such activities and firm performances such as markup or productivity.

Chapter 1 investigates the link between R&D and firm-level markups. A detailed data on R&D expenditures is used to examine whether a firm's innovation activities have any impact on its markups rather than productivity, whose relationship is already well-established in the literature. R&D is likely to help to differentiate a firm's products from those of other competitors, thus boosting its demand. However, this demand-enhancing aspect of R&D has not been thoroughly examined in the literature. With the consistent estimation of firm-level markups using a dataset of the Korean manufacturing firms, it is found that R&D increases firm-level markups, despite its size being small. To account for the fact that R&D is simply a measure of the innovation input, patent counts have been used as an alternative measure of innovation, but no evidence of positive effect was found. This may indicate that demand-enhancing innovations are not necessarily all patented, which may be due to various reasons.

Chapter 2 investigates the learning-by-exporting hypothesis. This has been widely researched in the current literature. However, this chapter places more focus on the estimation of productivity, which has been given little attention. In the learning-by-exporting hypothesis, it is theoretically suggested that productivity increases as a result of increase in efficiency. However, the conventional total factor productivity (TFP) measure contains information not only on efficiency but also on measurement errors and temporary shocks, the latter of which

is hardly related to the theoretical link between exports and productivity. In this chapter, a real total factor productivity that is derived as part of the semi-parametric estimation (denoted RTFP) is suggested as an alternative measure in which the latter elements above can be minimised. The findings show that, when RTFP is employed, the-learning-by-exporting effect is not only positive but also significant and long-lasting. However, this effect becomes short-lived and insignificant when the TFP is used. This does not necessarily suggest that the learning-by-exporting effect is better captured with the RTFP, but a certain measure, despite being not so relevant for productivity, can end up providing a misleading result. Moreover, the markups measure obtained from the first chapter are used to reconcile the fact that the productivity measure is measured by revenue data rather than quantity.

Chapter 3 examines the firm-level productivity, with much focus on offshoring. This chapter suggests modification to the Levinsohn-Petrin (LP) method to ensure alignment with the context of offshoring. This chapter suggests that value-added be used in place of gross sales when estimating a production function using the LP method to avoid inconsistent estimation in the second stage. The results show that offshoring has a positive impact on productivity, but the effect is not long-lasting. This suggests that offshoring can enhance productivity in the short-term by a composition effect in which resources are reallocated towards more productive activities or departments, whilst offshoring less productive ones to foreign vendors. The results also show that the modifications generate a significant difference in the estimators, suggesting the possibility of misleading results if no modification is made. RTFP, introduced in the second chapter, is also employed as a dependent variable and the results again display a highly significant effect of offshoring on productivity. As will be explained in the second chapter, RTFP is more fitting in measuring the trend of productivity, as it is designed to be less influenced by transitory shocks or measurement errors. Thus, the change in results indicates that the productivity-enhancing effect is clearer when using RTFP, however becomes less so when the conventional measure is employed. Moreover, the same estimates of markups from the first chapter are employed again to mitigate any bias arising from the demand-side.

Dedication

I dedicate this work to the Almighty God for giving me the opportunity and guiding my throughout my PhD degree. Also, to my family for their constant love and care and to my late grandfather for his unwavering support and motivation throughout my PhD.

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Chapter 1

R&D and Markups

1.1 Introduction

Returns to R&D have been a subject of considerable interest to academics, firm managers and policy makers alike, not least because the investment in R&D is expensive (Hall et al., 2010). Given the importance of innovation in the long-run economic growth, it is important to understand the returns to investments in R&D to provide them with reasons to consider undertaking such expensive investments.

The most widely-used method to measure the R&D returns is the framework developed by Griliches (1979). In his framework, the knowledge capital from R&D along with the physical capital is included in the production function after which it is then estimated. Under this production function framework, Hall and Mairesse (1995) displayed a positive link between R&D and productivity using the dataset of French manufacturing firms for the 1980s. Guellec and van Pottelsberghe (2002) also showed a positive impact of R&D investment on productivity growth based on a panel of 16 OECD countries.

However, in the literature, it is largely overlooked that output used in the estimation of productivity is sales or value-added. This implies that the returns to R&D come not only from a change in quantity but also from prices through innovation-driven demand. Process innovations from R&D are expected to enhance a firm's productivity by enabling larger quantities for each set of inputs[1][2]. Product innovation and qualitative improvements may affect

[1]According to the Oslo manual (OECD, 2005), a process innovation is defined to be the implementation of a new or significantly improved production or delivery method, including significant changes in techniques, equipment or software.

[2]The word "expected" implies that an investment in R&D does not necessarily translate into higher pro-

quantity[3], but are more concerned with price through the creation of demand (Mairesse and Mohnen, 2005). Differentiated goods will lower the elasticity of demand and, sequentially, the firm's market power resulting in the setting of higher price over marginal costs. This highlights the importance of investigating the effect of R&D on firm-level markups in order to examine the important, but largely overlooked, markup-enhancing aspect of R&D[4].

Successful R&D leads to the increase of markups either through prices or marginal costs[5]. While it is not possible to isolate the direct effect of R&D on prices due to data availability, a substantial impact is presumed to reflect onto the prices through demand creation for the discussion below. It is well known that firms tend to rely on R&D to differentiate their goods and services. Porter (1980) points out that firms adopting a differentiation strategy, compared to those pursuing cost leadership, are characteristic of high level of investment in R&D. Moreover, recent empirical finding from Jaumandreu and Mairesse (2017) shows that not only product but also process innovations are relevant for a shift in firm's demand, whereas process innovation does *not always* reduce marginal costs. This duly necessitates the need to examine the hypothesis that R&D enhances markups through differentiation. In section 1.7.4, any possible effect of R&D on markups through marginal costs will be controlled for as a part of robustness check.

This chapter contributes to the existing literature by adding to the scanty research on the markup-enhancing aspect of R&D. One of the reasons for the scantiness has stemmed from the fact that there is a lack of reliable data of firm-level prices or quantities. Geroski et al. (1993) investigated the effect of innovation on corporate profitability, however, Fisher and McGowan (1983) and many other scholars have already discussed the misuse of accounting profitability to infer economic profits[6]. In this regard, De Loecker and Warzynski (2012)

ductivity, but the positive link between process innovation and productivity is empirically supported by many studies (e.g. Crepon et al., 1998; Mairesse and Mohnen, 2005).

[3]New products can contribute to productivity-enhancing increased variety of intermediate inputs (Aghion et al., 1998).

[4]Cassiman and Vanormelingen (2014) focused on the link between innovation and firm-level markups. They use the information on innovation by directly asking yes/no type of questions to firms whether they have introduced any new or improved products or processes. The problem with this measure is that the answers to the question can be subjective, because the definition of innovation can be understood differently amongst the interviewees (Hall, 2011). Moreover, there is little or no screening undertaken by the database operators themselves, unlike with patents (Hagedoorn and Cloodt, 2003). This makes cross-firm comparisons extremely difficult.

[5]R&D may result in either product or process innovation. Product innovation is associated with a change in demand whereas process innovation is with a decrease in marginal cost.

[6]Schmalensee (1989) observed that large U.S. firms are more likely than small ones to adopt the accounting practices such as accelerated depreciation by which current profits become lower, troublingly without any consideration of the underlying economic phenomena. This is problematic because unobserved errors in the accounting data are likely to be correlated with regressors such as firm sizes, resulting in biased coefficients.

offered a method to directly estimate firm-level markups from the data. This chapter examines the link using a large dataset of Korean manufacturing firms, first by estimating firm-level markups and then by regressing them on the measure of R&D.

By focusing on the link between R&D and markups, this chapter will, as a corollary, contribute to shedding new light on the existing literature on R&D and productivity (e.g. Hall and Mairesse, 1995; Guellec and van Pottelsberghe, 2002). Due to the lack of data on firm-level prices and output quantities, revenue total factor productivity (TFPR) is often used in place of quantity total factor productivity (TFPQ)[7]. These two measures are correlated to a certain degree, but a high level of TFPR can be driven by high firm-specific demand rather than technical efficiency (Foster et al., 2008). Therefore, the link between R&D and markups, if established, will help to better understand the, almost unanimously positive, relationship between R&D and productivity established in the literature[8].

Furthermore, this chapter contributes to the literature by dividing R&D into in-house and offshore R&D. Outsourcing of R&D to low-cost countries is a relatively recent phenomenon, compared with that of tangible commodities (Lewin et al., 2009). Hence, little is known about the possible effects of offshoring R&D activities on firm performance, especially in terms of firm markups. Whilst R&D offshoring may help to boost markups by tapping into the technological capabilities of host countries, there is also a possibility of the loss of the offshoring firm's ability to keep pace with the rapidly evolving demand and preference of consumers when it becomes too reliant on foreign R&D suppliers.

The results in this chapter find that R&D significantly increases firm-level markups. In addition, R&D is found to significantly affect firm-level markups only when performed in-house. In the context of offshoring, however, it does not deliver the same effects, possibly due to increased costs of managing far-flung operations and added complexity. Furthermore, despite R&D being shown to be markup-enhancing, it is found that the effect does not uniformly apply across all industries, showing striking variations in the degree of effect from one industry to another.

The chapter is organised as follows. In section 1.2, the theoretical link between R&D and demand creation is described. Section 1.3 presents a brief description of the data used in this

[7]The use of TFPR as a proxy for TFPQ in the estimation is problematic. The related issues are examined in the following studies. See Klette and Griliches (1996) or Katayama et al. (2003).

[8]Foster et al. (2008) provided an important insight in this regard by using an unique data on producer-level prices and quantities. They differentiate TFPQ from TFPR and find that the latter is positively correlated with prices, whereas the former is inversely related with prices. This implies that TFPR, a oft-used measure in the literature, is more likely to be affected by a change in demand than productivity.

chapter. In section 1.4, the main empirical method to derive firm-level markups is described and its results are presented in section 1.5. In section 1.6, the regression of main interest is conducted to examine the link between firm-level markups and R&D. In section 1.7, a couple of extensions are made to the main regression introduced in section 1.6. The last section concludes the chapter.

1.2 R&D, Differentiation and Demand Elasticity

Unlike its appearance in the digitised dataset, R&D is a multi-faceted procedure. When a firm is said to have undertaken R&D, this entails the firm having engaged in basic or applied research to discover new knowledge, extend existing knowledge or produce specific inventions or modifications to existing techniques. It also includes the development of prototype designs and testing (OECD, 2005). Such diverse procedures help the firm to enhance its performances in two aspects.

Firstly, successful R&D activities enable a firm to produce greater volumes of output with the same set of inputs. As the stock of knowledge accumulates from R&D investments, this results in a greater level of output through the productivity enhancement. For this reason, in most empirical research, TFPQ is assumed to depend on the stock of R&D expenditure. As an increase in productivity indicates the use of fewer inputs in the production of each unit, this function of R&D is associated with a cost reduction.

Secondly, R&D allows a firm to produce a qualitatively differentiated output. To pull ahead of competitors, a firm is constantly motivated to differentiate its products from others by developing new products or services as well as adding improved features to existing ones. The unique selling points, thus created, will boost firm-specific demand and furnish the firm with a higher market power, despite still having little bearing on the improvement of technical efficiency. This effect is not captured in the conventional production function where quantities of physical inputs are related to quantities of output.

This second aspect of R&D is clearly distinguished from cost reduction that may arise from R&D. The firm-specific demand from a product differentiation results in a lower demand elasticity of a firm's products, hence higher markups (Appendix A.2). Taking an example of one imaginary beverage manufacturer; CamLiq, a local brewery, is imagined to manufacture beer for a long time. However, with many competing breweries in its vicinity, the resulting intense competition does not allow the brewery to increase its prices without fear of losing customers to its competitors. To escape competition, CamLiq invests a certain proportion of its profits into research in brewing chemistry. They resultantly find that adding hops at a later stage during brewing protects their aromatic oil and adds deep flavour to its finished beer. This new discovery helped to confer qualities on the brewery's existing portfolio that could not be rivalled by others, therefore enhancing CamLiq's markups.

Another such example can be seen through CamAuto, a Cambridge car manufacturer. It is reported to produce approximately 150,000 cars per year. Faced with competition from across the UK and abroad, the manufacturer takes the initiative to enhance its cars with a small gadget to monitor the driving decisions of drivers. Based on real time monitoring, the gadget advises those behind the wheel on optimal speeds or routes that produce the lowest fuel costs or driving time in real time. This technology-laden gadget brought additional features to the inherent value of cars by providing additional services to the existing products and, despite being a small addition, consequently, drew in a wider range of customers[9].

From the above examples, obvious technological changes were brought about in the products, which are not readily captured by the metrics of productivity such as TFPQ. This is because, even though a specific innovation was introduced, it comes with no overall change in the efficiency with which the inputs are used in production. In the first example, the beer is still produced using the same technique and ingredients with the only alteration being the timing at which the hops are added. Likewise in the latter instance, the cars are manufactured almost as efficiently as they were before servitisation is implemented. In both cases, monopoly rents are created in both products through differentiating them from other competing products in the market.

Schumpeter (1942) maintained that entrepreneurs, in the perennial gale of destruction, are constantly driven to capture monopoly rents by making qualitatively different products or services. This differentiation is especially important when competition is highly intense, as it allows a firm to pull ahead of a, possibly neck-and-neck, competition. The monopoly rents are earned by firms that are able to exercise market power. This market power is achieved by many factors such as government grants of exclusive rights (e.g. patent, trademark or copyright), control over the main distribution channels or a reputation or identity built through an advertising campaign (Kamien and Schwartz, 1982). However, when Schumpeter stressed the importance of entrepreneurship and a gale of creative destruction,

[9]R&D can accelerate servitisation by developing manufacturing-friendly technology such as artificial intelligence which can be bundled up with the existing products as part of enhanced services as described in the example.

he had the idea of adding value to products or services or the new combinations of resources. It is this very aspect of market power to which R&D can contribute.

In the economics literature, R&D is, more often than not, associated with the benefits of cost reduction. This can be partly due to the inclination to view the subject of technical change as the sole contributor to cost reductions. Rosenberg (1982) maintains that such a view is due to the tendency to accommodate a quantitative approach. As briefly mentioned above, a lack of data on firm-level prices or marginal costs prevents an estimation of the exact demand-enhancing aspect of R&D. The use of markups is only an indirect way to measure its impact on demand creation.

However, many studies have shown that R&D is associated more with price changes than with cost reductions. In the management literature, it is well established that a firm invests in R&D activities as a means of its differentiation strategy to develop unique products or services (Porter, 1980). Moreover, based on the data from 121 strategic business units, Govindarajan (1989) observed that R&D was positively associated with the implementation of a firm's differentiation strategy rather than a low-cost strategy.

1.3 Data

1.3.1 Survey of Business Activities

This chapter focuses on pooled cross-section samples of Korean manufacturing firms based on the Survey of Business Activities (SBA) that has been running from 2006 until 2015. The survey is annually conducted by the Statistics Korea (KOSTAT) and covers all enterprises with at least 50 employees or 300 million won capital. This chapter deals with only those within the manufacturing sector. The dataset is unbalanced due to the entering and exiting of businesses and contains information on approximately 5,700 firms per year on average in the manufacturing sector.

The SBA provides a wide range of financial statement-related data such as sales, wages, material costs, R&D, investments or tangible/intangible assets. The main variables which will be used in this chapter are briefly defined in Table 1.1. EMP is defined as the number of employees, whereas the remaining variables that are usually used in the estimation of production functions, such as RS,CAP or INT, are recorded in nominal values. Thus, they are deflated using the relevant price indices. RS refers to revenue, which is used as a proxy

Table 1.1: Variables and Definition

Variables	Definition
RS	The revenue deflated by price index
EMP	The number of employees
CAP	The capital deflated by relevant index
INT	The intermediate goods deflated by relevant index
RD	The R&D expenditure deflated by relevant index
RDSELF	The R&D expenditure performed in-house deflated by relevant index
RDOFF	The R&D expenditure performed offshore deflated by relevant index
GPC	The total number of patents granted and held
NPC	The total number of patents which are in actual use out of GPC
EXP	The dummy variable (1 = exporter, 0 = otherwise)
FOR	The dummy variable (1 = foreign-owned, 0 = otherwise)

Table 1.2: Summary Statistics of the Korean manufacturing firms during 2007-2015 : usual variables in the production function estimation

Year	RS	EMP	CAP	INT	Obs
2007	10.41	277	9.18	9.72	4,677
2008	10.60	292	9.36	9.90	3,602
2009	10.52	290	9.27	9.81	4,429
2010	10.71	288	9.42	10.00	4,238
2011	10.86	351	9.56	10.12	3,822
2012	10.81	327	9.57	10.06	4,303
2013	10.82	321	9.57	10.04	4,663
2014	10.84	329	9.66	10.07	4,509
2015	10.89	329	9.68	10.11	4,708

Note: All the values are expressed in logs with the exception of EMP.

for output and is deflated using the sector-level Producer Price Index (PPI) provided by the Bank of Korea. CAP and INT as well as the variables for $R\&D$ are deflated with the domestic PPI for capital goods and intermediate inputs that are also available from the same source.

Along with these standard variables, the SBA is especially rich in information on the measures of innovation activities: the innovation input or output. The information on the innovation input is presented in the form of the total amount of R&D spending. This information, in addition, divides the total spending into in-house (RDSELF) and offshore R&D spending (RDOFF). Moreover, the SBA provides information on the number of patents, an usual measure for the innovation output. Unlike the usual data on patent counts, that counts the number of patents granted to firms (GPC) regardless of their practicality or marketability

Table 1.3: Summary Statistics of the Innovation ariables

	RD	RDSELF	RDOFF	GPC	NPC
Total	6.21	6.20	5.27	1.58	1.49
Large	7.27	7.25	6.06	2.46	2.30
Small	5.76	5.76	4.62	1.25	1.18

Note: Large firms are defined to be the ones with employees over 200. On the other hand, small firms are the ones with 50 to 200 employees. All the values are expressed in logs. When taking logarithms of patents, the value of one is added to the number of patents because of the zeros in patents (Bloom et al., 2016).

Table 1.4: R&D Investing Firms' Share between 2007-2015 (%)

Year	(1)	(2)	(3)
2007	61.6	1.1	9.3
2008	63.5	1.1	9.9
2009	66.2	0.9	10.5
2010	62.6	1.1	7.7
2011	63.5	1.1	6.5
2012	67.6	0.9	5.7
2013	68.9	1.0	5.6
2014	71.3	0.9	5.9
2015	71.5	0.8	4.4

Note: (1) : The ratio of the number of firms investing only in in-house R&D to that of manufacturing firms (2) :The ratio of the number of firms investing only in offshore R&D to that of manufacturing firms (3) : The ratio of the number of firms investing both in in-house and offshore R&D to that of manufacturing firms

(e.g. Bloom et al., 2016), the SBA provides information on the number of patents that are in actual use (NPC)[10].

The summary statistics of firm-level variables used in the production function estimation are presented in Table 1.2[11]. The average values of real revenue, capital and intermediate inputs have all shown a broadly increasing trend over the sample periods, bar a temporary drop in the wake of the 2008 financial crisis. The increasing trend is also found in the employment variable, peaking at 351 in the year of 2011. The number has marginally dropped since then, however, it is difficult to infer the impact of any trend such as automation or offshoring purely from these readings. This is due to the constant exits and entries of firms over the

[10] All granted patents are no more than an indicator of the successful realisation of the technical requirements. According to the survey conducted by the Japan Patent Office (JPO), more than 60% of patents are not considered for internal use or license-out (Nagaoka et al., 2010). Not all patents are in actual use and, if they are not in use, it is hard to argue that they are, or at least have the potential of, contributing to firm's performances, albeit by varying degrees.

[11] The summary statistics start from 2007 instead of 2006, because the markups cannot be estimated for the very first year of the dataset. The information on the first year has been excluded in the estimation.

sample periods as shown from the number of firms.

Table 1.3 also reports the summary statistics of innovation variables such as R&D and patent counts. The often-used threshold of 200 employees is used to distinguish between large and small firms. By dividing the sample firms in this manner, it is observed that innovative activities - whether it be the input or output - are more active in larger firms than small. This is consistent with the Schumpeterian hypothesis that there is a positive link between firm size and innovation.

Table 1.4 shows the percentage share of firms investing in R&D between the period of 2007 and 2015. The first column shows the share of firms investing only in in-house R&D. Ranging from 61.6% in 2007 to 71.5% in 2015, a gradual increase is evident in the share. On the contrary, the share of firms investing solely in offshore R&D without investment in in-house R&D is as little as 1% and has not shown any significant change throughout the sample period. This indicates that very few firms opt to rely merely on offshored innovation activities, which is consistent with the empirical finding that complete reliance on the knowledge from external sources is unusual (Tether and Tajar, 2008) . The share of firms investing in both in-house and offshore R&D amounted to 9.3% in 2007, but has gradually decreased to 4.4% in 2015.

1.3.2 R&D Capital Stock

As Hall et al. (2010) noted, the underlying assumption behind the estimation of the effects of R&D is that R&D creates a firm-level stock of knowledge that creates demand into the future. The stock of knowledge created by R&D is computed by a simple perpetual inventory method (PIM). The PIM has been widely used in the literature due to its account for the depreciation of knowledge as in the case of physical capital (e.g. Coe and Helpman, 1995; Parisi et al., 2006). Denoting the stock arising from R&D investments as RDS, the formula for RDS is given as follows

$$RDS_{it} = \gamma_0 RD_{it} + \gamma_1 RD_{it-1} + \cdots + \gamma_T RD_{it-T} \tag{1.1}$$

where γ denotes the share of knowledge which is still in use. However, its exact share is not known and the assumption needs to be made that $\gamma_0 = 1, \gamma_1 = (1-\delta), \cdots, \gamma_T = (1-\delta)^T$, in which the depreciation rate, δ, is constant in every period t. Under this assumption, equation (1.1) can be transformed into the following equation

$$RDS_{it} = (1-\delta)RDS_{it-1} + RD_{it} \tag{1.2}$$

Many studies have assumed the depreciation rate, δ, for accumulated knowledge to be 15%, which is higher than the usual capital depreciation rate of 6%. This reflects the fact that technological obsolescence is significantly faster than capital depreciation (Ortega-Argilés et al., 2015). However, in this section, different depreciation rates are used depending on the technology intensity of sectors. This is based on the observation that more technologically intensive sectors are subject to faster technological progress than their less intensive counterparts, which in turn induces the faster obsolescence of the knowledge capital. In light of this, depreciations rates are assumed to be 15% for the low-medium tech industries and 18% for the high-tech sectors as suggested by Ortega-Argilés et al. (2015).

1.3.3 Measure of Market Structure

Among the control variables, which will be included in the regression, it is worth briefly commenting on the variable related to market structure. Markups can be assumed to be higher in a market with imperfect competition than the one close to perfect competition. The degree of competition is difficult to measure, but the Herfindahl index is often used (e.g. Aghion et al., 2005).

The Herfindahl index, denoted as HFI_{jt}, represents the degree of competition as measured by the market structure of industry j at time t. The index has long been used as a measure of concentration. It is calculated by the sum of squares of all firms' market shares in an industry as below

$$HFI_{jt} = \sum_{i=1}^{n}(s_{ijt})^2 \tag{1.3}$$

where s_{ijt} denotes the market share at firm i of industry j at time t. The lower the value of the index, the higher competition it implies amongst them. Squaring gives more weight to firms with a large market share than to those with a small share. Following Aghion et al. (2005), both the linear and quadratic terms of HFI_{jt} will be included.

1.4 Empirical Strategy

1.4.1 Markups

This section closely follows De Loecker and Warzynski (2012), which builds on the seminar work by Hall (1988), whose main argument is that the input's revenue share and cost share are the same under perfect competition[12], with the wedge between the two can being interpreted as the firm-level markups. However, neither the firm's total costs nor its returns to scale are easily measured or observed. De Loecker and Warzynski (2012) circumvented these issues by simply imposing a cost-minimising behaviour, resulting in the economisation of the required data. Firm-level markups are then obtained from the firm's cost minimising conditions for variable inputs which are free of adjustment costs. The output elasticity of a variable input is equal to that factor's expenditure share in total revenue only when $P = MC$. Any deviation from this should be regarded as a measure of the relevant markups. Consider a general production function of the form

$$Q_{it} = Q_{it}(L_{it}, M_{it}, K_{it}, \omega_{it}) \tag{1.4}$$

where Q_{it}, L_{it}, M_{it} and K_{it} denote output, labour, intermediate inputs and capital stock of a firm i at time t. $Q_{it}(\cdot)$ is a general production function whose only restrictions are to be continuous and twice differentiable with respect to its arguments. The first-order condition for a variable input M_{it} is

$$\frac{\partial Q_{it}(\cdot)}{\partial M_{it}} \frac{M_{it}}{Q_{it}} = \frac{1}{\lambda_{it}} \frac{P^M_{it} M_{it}}{Q_{it}} \tag{1.5}$$

where P^M_{it} denote a firm i's price for a variable input M at time t. λ_{it} denote the Lagrangian multiplier which is the marginal cost of production at a given level of output. Equation (1.5) shows that cost-minimising behaviour of a firm leads to the equality of the output elasticity of any variable input M_{it} to $\frac{1}{\lambda_{it}} \frac{P^M_{it} M_{it}}{Q_{it}}$. Subsequently, by defining the markup as μ_{it} as $\mu_{it} \equiv \frac{P_{it}}{\lambda_{it}}$., equation (1.5) can be re-written as below

[12] The markup is defined to be the revenue ($P_{it}Q_{it}$) divided by the total costs ($Q_{it}AC_{it}$). This is based on the fact that, under constant returns to scale, marginal costs are equal to average costs ($AC_{it} = MC_{it}$). Alternatively, this can also be expressed as the ratio of the input's cost share ($w_{it}L_{it}/TC_{it}$) to the input's revenue share ($w_{it}L_{it}/P_{it}Q_{it}$), where the input is labour and TC denotes the total costs. Theoretically, they measure the same values.

$$\theta^M_{it} = \mu_{it} \frac{P^M_{it} M_{it}}{P_{it} Q_{it}} \tag{1.6}$$

where θ^M_{it} denotes the output elasticity of an input M. The data on total sales ($P_{it}Q_{it}$) and the expenditure on intermediate inputs ($P^M_{it}M_{it}$) can be easily obtained from the dataset, whereas the output elasticity θ^M_{it} is not. Its consistent estimation is the main concern in the next section.

1.4.2 Output Elasticities

Output elasticities are estimated from the semi-parametric production function estimation methods such as Olley and Pakes (1996) (OP) or Levinsohn and Petrin (2003) (LP). To apply these methods, two additional assumptions need to be imposed on the production function. First, productivity is assumed to be Hicks-neutral. Second, production function parameters are assumed identical across all firms. With these assumptions, a log version of equation (1.4) can be expressed as

$$q_{it} = f(l_{it}, m_{it}, k_{it}; \beta) + \omega_{it} + \epsilon_{it} \tag{1.7}$$

where $q_{it} = \ln Q_{it}$ and l_{it}, m_{it} and k_{it} denote logged labour, intermediate inputs and capital of firm i and time t respectively. ϵ_{it} implies that the measurement error in output and unanticipated shocks are implicitly allowed for, whereas ω_{it} denote the level of productivity observable to the firm, but not to the econometrician, when making a decision on the level of inputs. Departing from the Cobb-Douglas functional form, the production function $f(\cdot)$ is approximated by translog specification. This enables the obtainment of different markups across firms within one industry and to avoid a situation in which any variation in markup is attributed to the change in the input's revenue shares.

As the decision on variable inputs is determined after observing ω_{it}, there is a possibility of simultaneity bias. The simultaneity bias can be circumvented by employing the idea that the optimal choice of variable inputs depends on the level of productivity. As in LP, the demand function for intermediate inputs, $m_{it} = m_t(k_{it}, \omega_{it}, \mathbf{z}_{it})$, is used to control for unobservable productivity ω_{it}. This can be done by inverting out the demand function and replacing ω_{it} with the inverted demand function. Consequently, equation (1.7) can be re-expressed as below[13]

$$q_{it} = f(l_{it}, m_{it}, k_{it}; \beta) + h_t(k_{it}, m_{it}, \mathbf{z}_{it}) + \epsilon_{it} \tag{1.8}$$

where $h_t(\cdot) = m_t^{-1}(\cdot) = \omega_{it}$. $\mathbf{z}_{it}$ denote additional variables which could potentially affect optimal input demand across and within firms over time. De Loecker and Warzynski (2012) indicated that the inclusion of these additional variables in the estimation routine obviates the need for taking a stand on the exact model of competition. The usual OP or LP proceeds in two stages, recovering the coefficients of variable inputs and that of capital in the first and second stages respectively.

However, this section takes heed of the critique of Ackerberg et al. (2006) and identifies no parameters in the first stage. According to the critique (see Appendix A.1), the collinearity problem that l_{it} does not vary independently of the non-parametric function makes identification of the coefficient β_l not plausible in the first stage. In the first stage, the regression equation is

$$q_{it} = \phi_t(l_{it}, k_{it}, m_{it}, \mathbf{z}_{it}) + \epsilon_{it} \tag{1.9}$$

where $\phi_{it} = \beta_l l_{it} + \beta_m m_{it} + \beta_k k_{it} + \beta_{ll} l_{it}^2 + \beta_{mm} m_{it}^2 + \beta_{kk} k_{it}^2 + \beta_{lk} l_{it} k_{it} + \beta_{lm} l_{it} m_{it} + \beta_{mk} m_{it} k_{it} + h_t(k_{it}, m_{it}, \mathbf{z}_{it})$. In the first stage, estimates of ϕ_{it} and ϵ_{it}, that is, $\hat{\phi}_{it}$ and $\hat{\epsilon}_{it}$ respectively, are obtained. In the second stage, all the coefficients are recovered by relying on the following first-order Markov process of ω_{it}

$$\omega_{it} = g_t(\omega_{it-1}) + \zeta_{it} \tag{1.10}$$

where $g_t(\cdot)$ is an unknown function and ζ_{it} the innovation to productivity. An estimate for $\zeta_{it}(\beta)$ is retrieved by non-parametrically regressing $\omega_{it}(\beta) = \hat{\phi}_{it} - \beta_l l_{it} - \beta_m m_{it} - \beta_k k_{it} - \beta_{ll} l_{it}^2 - \beta_{mm} m_{it}^2 - \beta_{kk} k_{it}^2 - \beta_{lk} l_{it} k_{it} - \beta_{lm} l_{it} m_{it} - \beta_{mk} m_{it} k_{it}$ on $\omega_{it-1}(\beta)$, given β[14]. The retrieved estimate for ζ_{it} is then used to construct the sample analogue of the following moment conditions

$$E[\zeta_{it}(\beta)\mathbf{h}_{it}] = 0 \tag{1.11}$$

[13] If the demand for intermediate inputs strictly increases in productivity conditional on other state variables, the invertibility of intermediate inputs function is ensured.

[14] A vector of input coefficients β is obtained from the OLS estimation of the equation (1.8).

where $\mathbf{h}_{it} = \{l_{it-1}, m_{it-1}, k_{it}, l_{it-1}^2, m_{it-1}^2, k_{it}^2, l_{it-1}k_{it}, l_{it-1}m_{it-1}, m_{it-1}k_{it}\}$ is the set of instruments with the assumption that capital is quasi-fixed. The estimated output elasticities are then obtained by

$$\hat{\theta}_{it}^M = \hat{\beta}_m + 2\hat{\beta}_{mm}m_{it} + \hat{\beta}_{lm}l_{it} + \hat{\beta}_{mk}k_{it} \tag{1.12}$$

This shows the strength of trans-log production function as output elasticities can vary across firms depending on the level of their other input use, despite production function coefficients being assumed to be equal across firms.

Before proceeding further into the results, it needs to be reminded that a measure of output is not quantity but sales deflated using industry-level price index. This can result in omitted price variable bias as discussed in (Klette and Griliches, 1996; Katayama et al., 2003). This is a common occurrence as the data on physical quantities and prices are seldom available. A few comments could be made regarding this potential omitted price variable bias. First, the use of proxy for productivity in the estimation of production function helps against unobserved prices (De Loecker and Warzynski, 2012). The proxy will control for any price variation correlated with the variation of productivity, removing its impact on the estimation of the production function. Second, the previous point will not be valid should any price variation be correlated with demand shocks that are not correlated with productivity. Then, unobserved prices will bias the level of the markup, possibly downwardly. However, even this will not affect the estimates in this chapter if such bias is not systematically related to the firm's R&D activities subsequent to controlling for differences in input use (De Loecker and Warzynski, 2012). Lastly, there are a few empirical findings that there is less impact from unobserved prices than the omitted price variable bias predicts. Mairesse and Mohnen (2005) found that moving from industry-level price deflator to firm-level deflator does not alter the estimated output elasticities. De Loecker and Warzynski (2012) also empirically confirmed that their main estimates are not affected by unobserved prices.

1.5 Results

1.5.1 Output Elasticities

From the estimation procedure described above, the output elasticities are recovered from the gross output trans-log production function. The production function is estimated sep-

Table 1.5: Average Output Elasticities, By Industry

Industry	Labour	Materials	Capital	No. of Obs.
13	0.28	0.53	0.07	1874
17	0.20	0.67	0.10	1105
20	0.15	0.67	0.11	2881
22	0.26	0.59	0.07	3118
23	0.23	0.53	0.17	1522
24	0.15	0.67	0.08	2711
25	0.30	0.52	0.16	2714
26	0.30	0.56	0.07	5891
27	0.31	0.52	0.12	1538
28	0.20	0.68	0.05	2753
29	0.32	0.49	0.11	5264
30	0.22	0.59	0.10	5771
31	0.23	0.41	0.20	928
32	0.19	0.73	0.16	418
33	0.21	0.59	0.13	463

arately for each industry. As briefly mentioned above, the use of the translog production function allows output elasticities to vary across firms. Table 1.5 reports the average output elasticities across the industries.

The Korean manufacturing sector is divided into 15 different industries. There are wide differences in the output elasticities not only across firms but also across industries. It is indicated that the output elasticities of labour range from 0.15 to 0.32 and those of capital from 0.07 to 0.20, with materials contributing the largest role in production, ranging from 0.41 to 0.73[15].

As the mean statistic is likely to be affected by outliers in each industry, Table 1.6 additionally reports the median output elasticities in its comparison. This indicates that there are differences between the mean and median elasticities, which shows the possibility that the average output elasticities are influenced by outliers. However, the difference between the values is not wide.

Table 1.7 shows that industry-average returns to scale amount to 0.93 and the median is 0.92. This is in line with the findings of De Loecker et al. (2016). Since the returns to scale are allowed to vary across firms, a proportion of them can still exhibit increasing returns to scale. It is found that the proportion amounts to 68 % in the Indian firm-level production

[15] In Table 1.5, the wearing apparel industry (14) was excluded because nonsensical negative output elasticities were reported. However, the exclusion has not changed the overall result probably because of its small sample size.

Table 1.6: Median Output Elasticities, By Industry

Industry	Labour	Materials	Capital
13	0.27	0.53	0.08
17	0.19	0.68	0.11
20	0.14	0.65	0.11
22	0.25	0.58	0.08
23	0.22	0.53	0.17
24	0.15	0.66	0.08
25	0.29	0.52	0.16
26	0.29	0.55	0.08
27	0.30	0.52	0.13
28	0.19	0.67	0.05
29	0.31	0.49	0.11
30	0.21	0.57	0.10
31	0.24	0.39	0.18
32	0.17	0.72	0.16
33	0.18	0.59	0.16

data. However, in Korean manufacturing, only 27.6 % of the sample exhibits increasing returns to scale. This pales in comparison to the finding of De Loecker et al. (2016).

Table 1.7: Returns to Scale, Mean and Median

Returns to Scale	Mean	Median
De Loecker et al. (2016)	0.95	-
All	0.93	0.92
Large Firms	1.09	1.07
Small Firms	0.88	0.88

* Large firms are defined to be the ones which employ more than 200 employees whereas small firms are the ones with less than 200 employees. Returns to scale are the sum of output elasticities of labour, materials and capital.

If the data is divided into two groups - large and small firms - depending on the number of employees, it is clear that there is a large difference in the returns to scale between them. The average returns to scale for large firms amount to 1.09, whereas those for small firms are only 0.88. This is in line with empirical findings in which small firms operate under decreasing returns to scale (e.g. Halpern and Korösi, 2001).

Table 1.8: Estimate of Markups, Whole Industry

	Mean	Median.
	1.34	1.17
South Korea*	1.48	-
Asia*	1.45	-
Global*	1.59	-
Large Firms	1.51	1.26
Small Firms	1.27	1.10

* These estimates are from De Loecker and Eeckhout (2018). They are calculated based on the Worldscope dataset which contains financial statements for over 70,000 companies worldwide. The values are the average markup in 2016.

1.5.2 Markups

In Table 1.8, the first row reports the estimates of industry-mean and -median markups. The mean markup is seen to equal to 1.34 and the median amounting to 1.17. The mean value is marginally lower than the Korean industry-average markup of 1.48 reported in De Loecker and Eeckhout (2018). The mean value is also smaller in comparison to the Asian and Global average markups in the third and fourth rows respectively. However, it should only be noted that the latter values are the average value of the markups only in 2016 whereas the mean value in the first row is the average of the markups between 2007 and 2015. De Loecker and Eeckhout (2018) indicated that the global markup has increased from 1.1 in 1980 to around 1.6 in 2016[16].

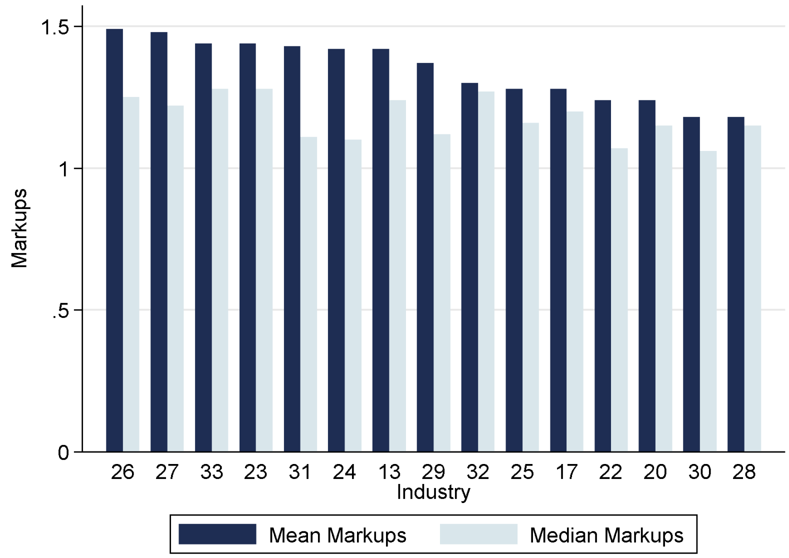
Figure 1.1 displays the mean and median of markups across industries are reported in navy and pale blue bars respectively. It is evident that there is no marked difference seen between the mean and median markups in almost every industry. However, the median values are generally lower than the mean values, notably in furniture (31) and basic metals (24). This indicates the possibility that the average markups are likely to be driven by outliers to a certain degree.

Markups can be seen to be greater than unity in all the industries, ranging from 1.18 to 1.49. The industries with the highest markups are computer, electronic and optical products (26) and electrical equipment (27), whereas those with the lowest markups are machinery and equipment (28) and other transport equipment (30).

The time-trend of the mean and median markups is plotted in Figure 1.2 (a) and (b) respec-

[16]According to De Loecker and Eeckhout (2018), the mean markup of 1.34 is in line with those of Finland (1.36), Austria (1.34), Germany (1.35), India (1.32), Japan (1.33) or New Zealand (1.35).

Figure 1.1: Mean and Median Markups Across Industries



tively. Cassiman and Vanormelingen (2014) pointed out that markups are empirically found to be strongly pro-cyclical, with the evolution of both markups being consistent with this observation. The markups were seen to be high before the crisis, but dramatically declined in the run up to the financial crisis. This decreasing trend was reversed shortly after the crisis according to Figure 1.2 (a), whereas the markups almost continuously decreased until 2011 according to Figure 1.2 (b). This difference may suggest that firms with significantly large markups are generally more resilient to the external shocks such as financial crises, boosting the average markups. In both cases, the time-trend of markups has shown an U-shaped evolution, implying that they are on the recovery since the financial crisis.

1.6 Markups and R&D

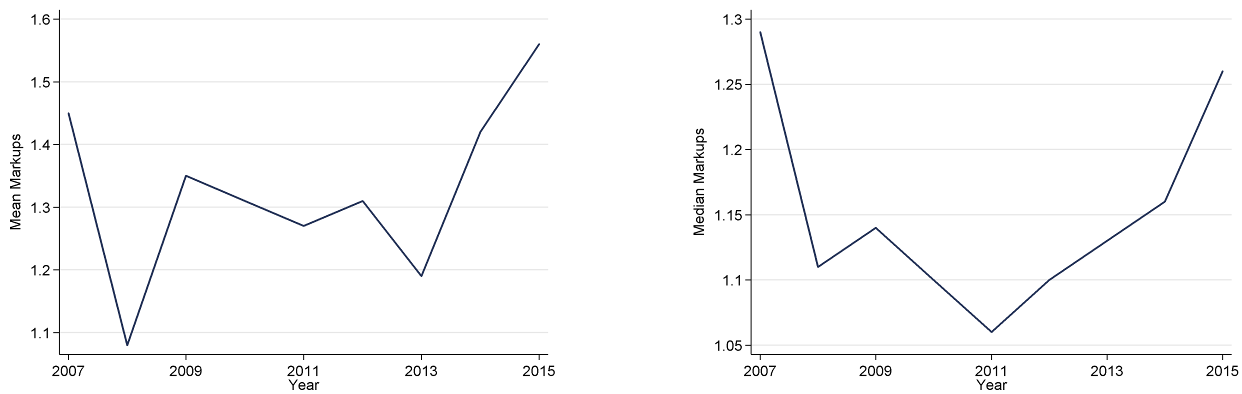
In this section, the regression of the firm-level markups on R&D is estimated, with the following regression equation being considered,

$$\log \mu_{it} = \beta_0 + \beta_1 RDSI_{it} + \mathbf{X_{it}}\gamma + \delta_{\mathbf{j}} + \delta_{\mathbf{t}} + \epsilon_{\mathbf{it}} \tag{1.13}$$

where μ_{it} denotes firm-level markups of firm i at time t and $RDSI$ denote (logged) R&D intensity calculated as the ratio of the R&D capital stock to the firm's sales. There are a few identification issues that need to be discussed to identify the relationship between firm-

Figure 1.2: Evolution of Mean and Median Markups

(a) Mean Markups (b) Median Markups



level market power and the innovation input. Firstly, there can be macroeconomic factors that affect both innovation and firm-level market power which change over time. If these are not controlled for, there is a possibility that the resulting significant coefficient can be spurious. Therefore, time-specific fixed effects (δ_t) are included. Secondly, there may be industry-specific factors. These industry-level differences may account for discrepancies in innovative activities which cannot be explained by firm-level markups. Therefore, in order to control for industry-level heterogenity, industry-level fixed effects (δ_j) are also included. X_{it} denotes a vector of control variables such as firm's exporting (De Loecker and Warzynski, 2012) or offshoring status. In addition, the variables such as market structure and firm size are also included.

Results from Ordinary Least Squares (OLS) can be seen in Table 1.9. The specification in column (1) indicates that there is, on average, a 0.59% increase in markup if R&D intensity increases by 10%. The coefficient is highly significant even under 1% level of significance, but is difficult to be described as sizeable. The specifications in columns (2) and (3) include a dummy indicating whether the firm is an exporter or offshorer and other control variables respectively. However, there is no noticeable change in the coefficient on R&D capital stock. The results therefore show that R&D is likely to have a positive association with firm-level markups.

The coefficients on the control variables in Table 1.9 display the expected signs, with a firm's size and its markups having a significant and positive association. Furthermore, the market concentration, as measured by the Herfindahl index, shows a positive effect on firm-level

Table 1.9: Regression of Markups on R&D : Ordinary Least Squares (OLS)

	(1)	(2)	(3)
$RDSI$	0.059^{***}	0.055^{***}	0.055^{***}
	(0.002)	(0.002)	(0.002)
$SIZE$	0.115^{***}	0.127^{***}	0.127^{***}
	(0.002)	(0.002)	(0.002)
HFI	0.428^{***}	0.419^{***}	1.245^{***}
	(0.036)	(0.036)	(0.122)
$HFISQ$			-1.926^{***}
			(0.272)
EXP		-0.114^{***}	-0.114^{***}
		(0.004)	(0.004)
OFF		0.098^{***}	0.097^{***}
		(0.009)	(0.002)
Industry	Yes	Yes	Yes
Year	Yes	Yes	Yes
R^2	0.125	0.142	0.143
Observation	34,145	34,145	34,145

Note: Standard errors are reported in parentheses. ***,** and * indicate significance at 1%, 5% and 10% respectively.

markups. The Herfindahl indices measure the concentration of an industry, where a high level of concentration indicates that there are only a few large firms that hold a large percentage of the market. Interestingly, the inclusion of a squared Herfindahl index in column (3) shows that there is an inverted-U relationship between firm-level markups and market concentration.

Dummies included in specification (2) indicate that there is no premia for exporters. Rather, it can be seen that exporters tend to have, on average, 11.4% lower markups than those with no exporting. This is not consistent with the findings of De Loecker and Warzynski (2012). This lower makrup may be explained by the fact that exporters tend to face more competition than those only operating in the domestic market. On the other hand, offshorers tend to have on average 9.8% higher markups than those with no offshoring. Although there is no empirical research on the link between offshoring and markups, the positive association is consistent with the fact that offshoring is fundamentally the substitution of in-house activities for those provided by outside contractors, often at cheaper prices. The inclusion of these dummy variables, however, does not affect the size or significance of the coefficient on R&D.

Table 1.10 includes R&D intensity variables with various lag structures. Thus, in columns

Table 1.10: Regression of Markups on R&D : Different Lag Structures

	(1)	(2)	(3)
$L1.RDSI$	0.053^{***}	0.049^{***}	0.049^{***}
	(0.002)	(0.002)	(0.002)
$L2.RDSI$	0.049^{***}	0.046^{***}	0.046^{***}
	(0.002)	(0.002)	(0.002)
$L3.RDSI$	0.047^{***}	0.043^{***}	0.043^{***}
	(0.002)	(0.002)	(0.002)

Note: Standard errors are reported in parentheses. ***,** and * indicate significance at 1%, 5% and 10% respectively.

(1) - (3) of Table 1.9, the R&D intensity variable is lagged by one to three years respectively (denoted by L followed by the number of lags). Despite the coefficient showing marginal decreases as further lags are considered, they are seen to be largely constant and all highly consistent under 1% level. This indicates that the use of R&D capital stock results in the consideration of the lag structure more ore less redundant as the past values of R&D investments have already been incorporated into the R&D stock variable. The effects from R&D do not solely result from current or lagged flows of R&D but from accumulated stock of knowledge from a series of R&D investments.

However, the OLS can be a naive approach as it is likely that there are unobservable factors (e.g. the presence of innovative managers in a firm) which can affect both firm-level makrkups and R&D intensity, leading to biased coefficients. Similarly, there may be a reverse causality running from firm-level markups to R&D intensity. To overcome the possible endogeneity, fixed-effects regression has been employed by assuming that such unobservable firm-level characteristics are time-invariant. The results in column (1) of Table 1.11 indicate that the effect of R&D on firm-level markups remains positive and significant under 1% level of significance.

To further control for endogeneity, the system-GMM method has been used to estimate the dynamic equation (1.14) as below.

$$\log \mu_{it} = \beta_0 + \beta_1 \log \mu_{it-1} + \beta_2 RDSI_{it} + \mathbf{X_{it}}\gamma + \delta_\mathbf{i} + \delta_\mathbf{t} + \epsilon_\mathbf{it} \tag{1.14}$$

where μ_{it-1} is the lagged dependant variable. In this case, applying OLS to (1.14) will lead to inconsistent estimation of the coefficients as δ_i is correlated with the lagged dependent variable. Although the usual fixed-effects estimator eliminates δ_i, the lagged dependent

Table 1.11: Regression of Markups on R&D : Fixed Effects (FE) and Generalised Method of Moments (GMM)

	(1)	(2)	(3)
	FE	FE	GMM-SYS
$L.\log\mu$		0.330^{***}	0.559^{***}
		(0.005)	(0.113)
$RDSI$	0.024^{***}	0.029^{***}	0.086^{***}
	(0.002)	(0.002)	(0.028)
Industry	Yes	Yes	Yes
Year	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observation	34,145	27,218	27,218
AR(1)			0.000
AR(2)			0.386
Hansen			0.379

Note: Standard errors are reported in parentheses. ***,** and * indicate significance at 1%, 5% and 10% respectively. The Hansen test is used to test the null hypothesis that the instruments are valid. The AR test is used to find the evidence of autocorrelation in the errors. The same control variables are included as in Table 1.9.

variable is still correlated with the error term $(\epsilon_{it} - \bar{\epsilon}_i)$.

Inconsistency can only be ameliorated if long panels induce $\bar{\epsilon}_i$ to shrink. Nickell (1981) demonstrated that the inconsistency is sizeable in short panels as it is of order T^{-1} as $n \to \infty$ (when T denotes time periods and n the number of observations). As the data in this chapter is essentially short panels, inconsistency is inevitable if fixed effects estimation is employed. To overcome this, Arellano and Bond (1991), Arellano and Bover (1995) and Blundell and Bond (2000) have suggested instrument variables method designed for situations with few time periods and many panels.

Arellano and Bond (1991) proposed using lagged levels as the instruments for differenced variables, hence the name *difference GMM (DGMM)*. Subsequently, Arellano and Bover (1995) and Blundell and Bond (2000) had noted that the lagged levels may serve as poor instruments for first differenced variables, especially if the variables are close to a random walk. Hence, this led them to modify DGMM and introduce the original equation back to the differenced equation and build a system of equations. Hence, the name *system GMM (SGMM)* (Appendix A.3 for more detail), proposing to use both lagged levels and lagged differences as the instruments. The latter method circumvents the dilemma of weak instruments in DGMM by combining the moments conditions for the levels equation and those for the first differenced equation. Thus, these newly added moments can increase efficiency.

In the estimation of equation (1.14) using SGMM, the second and earlier lags were used as instruments for the differenced equation, whereas lagged first-differences were used as instruments for the level equation. The results are reported in the third column of Table 1.11, as the current instrumentation passed the necessary tests.

Column (2) of Table 1.11 reports the results of equation (1.14) using fixed effects estimator. The coefficient on R&D intensity can be seen to have increased to 0.029 and remains consistent with the previous results in that it is positive and highly significant even under 1% level. Column (3) reports the results from SGMM using the lagged difference in markups and R&D as well as the lagged levels as instruments. The coefficient on R&D intensity has increased to 0.086 and remained significant at the 1% level. This suggests that there is a strong evidence of markup-enhancing effects of R&D and the overall results do *not* depend substantially on the estimation techniques, despite marginally varying in magnitude.

1.7 Extensions

1.7.1 R&D Offshoring

In the previous regression, the R&D capital stock relative to real sales was used as a regressor. However, this can be divided into two types of R&D capital stock; R&D capital stock from R&D performed in-house ($RDSELF$) and R&D capital stock from R&D performed offshored ($RDOFF$). R&D is usually recognised as firm-level activities centralised in the home country, but there has been a trend towards offshoring R&D activities either to foreign affiliates or third parties in the foreign country (Castellani and Pieri, 2013).

Picci (2010) noted that globalisation has made inroads into as far as the firm's innovative activities such as R&D. Guellec and van Pottelsberghe (2001) documented the cases where the inventor and the applicant of a patent do not reside in the same country to show increasing trends in the internationalisation of R&D[17]. It is not only tangible commodities, but also research activities that have been outsourced to low-income countries (Lewin et al., 2009).

The macro-level research on the effects of foreign R&D on the home country such as domestic productivity is not new. Coe and Helpman (1995) found that foreign R&D has a positive impact on domestic productivity. Van Pottelsberghe De La Potterie and Lichtenberg (2001)

[17]Guellec and van Pottelsberghe (2001) argue that these patents, in a majority of cases, reflect the fact that R&D is being performed in a research facility abroad of a firm.

Table 1.12: Regression of Markups on R&D Offshoring : OLS, FE and GMM

	(1) OLS	(2) FE	(3) FE	(4) GMM-SYS
$L.\log\mu$			0.330***	0.452***
			(0.005)	(0.040)
$RDSELF$	0.053***	0.023***	0.028***	0.077***
	(0.002)	(0.002)	(0.002)	(0.016)
$RDOFF$	0.023***	0.010***	0.008***	0.016*
		(0.002)	(0.002)	(0.009)
Industry	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observation	34,145	34,145	27,218	27,218
AR(1)				0.00
AR(2)				0.13
Hansen				0.19

Note: Standard errors are reported in parentheses. ***,** and * indicate significance at 1%, 5% and 10% respectively. The Hansen test is used to test the null hypothesis that the instruments are valid. The AR test is used to find the evidence of autocorrelation in the errors.

also showed that foreign R&D affects domestic performance through trade flows or outward foreign direct investment (FDI). In this line of literature, the transfer of knowledge generated in the foreign R&D is assumed to indirectly take place through either FDI or trade flows. Such transfer processes would be more direct in the case of firm-level R&D offshoring as it is intended to generate knowledge which will be directly used by the offshoring firm.

There are various motivations behind R&D offshoring such as the need to implement a faster and cheaper innovative process (Castellani and Pieri, 2013). This especially applies to those firms whose comparative advantages do not lie in innovative activities and, therefore, which offshore R&D to external arm's length contractors. R&D offshoring, in this context, refers to "the contractually agreed, non-gratuitous and temporary performance of R&D tasks for a client" (Grimpe and Kaiser, 2010, p.1484). It can also be offshored to foreign affiliates with a view to modifying its products or processes to render them more appropriate to local conditions as well as sourcing technologies of other firms either through spillovers or R&D alliances (Criscuolo et al., 2005)[18]. These two types of R&D offshoring may have varying

[18] Criscuolo et al. (2005) denoted R&D with the former motivation as asset-exploiting R&D and that with the latter motivation as asset-augmenting R&D. The latter type of R&D is especially relevant when the knowledge in point is geographically 'sticky' (Criscuolo et al., 2005). This becomes all the more relevant for the case of tacit knowledge. Polanyi (1966), the founding father of the concept of tacit knowledge, defined it as "an *actual knowledge* that is indeterminate, in the sense that its content cannot be explicitly stated (p.4)." Stored in human beings in the form of of know-how, expertise, experience or insight, it is not easily transferred because

effects on firm performance, but unfortunately the current dataset do not have relevant information.

On the other hand, there has been a discussion on the negative sides R&D offshoring may bring on a firm's productivity or employment (e.g. Pisano and Shih, 2009). As the internalisation of R&D increased, it was even suggested that the relocation of R&D abroad may weaken the innovative capabilities as well as the national innovation system ultimately (Criscuolo, 2009). However, the related literature generally confirms the positive impact of R&D offshoring on the home country innovation or productivity (e.g. Criscuolo et al., 2005; Criscuolo, 2009; Castellani and Pieri, 2013) [19].

This chapter looked at the issue from a different perspective by focusing on the effect of R&D offshoring on firm-level markups. This investigation attempts to find out which stocks of knowledge - generated from in-house R&D expenditures or offshore R&D expenditures - are more effective at enhancing a firm's markups. The regression equations (1.13) and (1.14) are estimated with two different types of R&D capital stock, that is, $RDSELF$ and $RDOFF$. The results are presented in Table 1.12.

Results from OLS reported in column (1) indicate that both in-house and offshore R&D significantly increase firm-level markups. The coefficients are significant under 1% level of significance, with the coefficient on $RDSELF$ being more than twice as large than that on $RDOFF$. Column (2) reports results using the fixed effects estimator. The coefficients on both variables have more than halved, but still remain highly significant under 1% level. These findings suggest that the stocks of knowledge from R&D, whether they be accumulated from in-house or offshore R&D, positively contribute to firm-level markups.

Column (3) estimates the dynamic regression using fixed effects, yielding the results similar to the previous ones. However, these results are likely to be biased. Column (4) reports the results from SGMM using the lagged difference in markups and R&D as well as the lagged levels as instruments. The coefficient on $RDSELF$ is seen to have increased to 0.77 and remained significant at the 1% level. However, the coefficient on $RDOFF$ shows to only be marginally significant under 10% level, despite still remaining positive. These findings

it cannot be explicitly documented or articulated. Thus, its effective transmission is highly reliant on spatial proximity (Gertler, 2003). The former type of R&D has some direct relevance for demand-side considerations and the latter type will also indirectly have impact on demand creation.

[19] Criscuolo et al. (2005) and Criscuolo (2009) confirmed the existence of a reverse knowledge flow from a multinational enterprise (MNE)'s foreign based R&D facilities to its home country firms, based on their patent citation analysis. Moreover, Castellani and Pieri (2013) found evidence for positive link between R&D offshoring and the home *region* productivity growth.

suggest that R&D significantly increases firm-level markups when conducted in-house, but has only marginally positive effect on markups when offshored.

In terms of how the results can be interpreted, the data availability makes it difficult to provide a complete answer. For example, the effects could differ depending on the types of offshoring - whether R&D is offshored to the firm's own foreign affiliates or to arm's length suppliers. Unfortunately, the current dataset does not provide such detailed information. Given that there is only a handful of MNEs in the Korean manufacturing sector, the following candidate explanations are presented with the assumption that R&D was offshored to arm's length contractors in the majority of cases.

Firstly, it is likely that R&D, when offshored, results in the loss of the offshoring firm's ability to keep abreast of technologies used for design and manufacturing (Kotabe, 1998). This may be due to the dilution of firm-specific resources in the process of R&D offshoring and reliance on rather generic external knowledge to which potential competitors may also have access to (Grimpe and Kaiser, 2010). This will limit the firm's capacity to differentiate its products from its competitors' and eventually weaken the link between R&D and demand creation.

Secondly, the stock of knowledge generated abroad cannot even be utilised if R&D offshoring renders the deterioration of a firm's capability to tailor external knowledge resources to firm-specific needs (Grimpe and Kaiser, 2010). The knowledge generated from R&D has the characteristic of being tacit, but the loss of proximity due to offshoring can affect the ability to transfer this tacit knowledge between the firm and the R&D contractor.

Finally, there is a possibility that costs from R&D offshoring could outweigh its benefits. **?** maintained that the process of fragmentation involves more complexity and costs in terms of added efforts of management and communication, as well as search and transaction costs. Given these factors, there is a possibility that offshoring R&D does not contribute as much to firm-level markups as that performed in-house.

1.7.2 Technology Intensity and the Effects of R&D

OECD suggests classifying industries into "high", "medium-high" and "low technology" depending on R&D intensity (see Appendix A.4). Based on this classification, the entirety of Korean manufacturing can be classified into three different groups based on R&D relative to revenue statistics. It does not require much exaggeration to hypothesise that technology-intensive industries have more room for improvement in terms of productivity or markups

Table 1.13: R&D and Markups : Technology Intensities

	(1) Low	(2) Medium-High	(3) High
$RDIS$	0.012**	0.007***	0.035***
	(0.004)	(0.002)	(0.003)
Industry	Yes	Yes	Yes
Year	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	3,988	8,631	18,825

Notes : Standard errors are reported in parentheses. * 10%, ** 5%, *** 1% level of significance.

when an equal level of resources are allocated to R&D, compared to low-technology industries.

The regression of firm-level markups on R&D intensity can be estimated using fixed-effects for each group separately and the results can be seen in Table 1.13. As in the previous regressions, the same control variables and both year and industry dummies have been included.

The coefficients on $RDIS$ are shown to be positive and significant in every group, being highest in high technology industries. These findings have implications suggesting that, despite R&D having markup-enhancing effects, the degree of effects can vary depending on the industries. It is expected that markup-enhancing effects will be largest, if there are more rooms for upgrading designs or technologies. As expected, such effects are seen to be highest in industries with high technology relative to the low-technology industries.

Table 1.14 reports industry-by-industry regression of markups on R&D. The results confirm the hypothesis that R&D has varying effects on firm-level markups depending on the industries. The markup-enhancing effects are shown to be highest in industries such as Computer and Electronic Products or Electrical Equipment, both of which belong to high-tech industries. However, the effects are significantly low in Textiles or Rubber and Plastic Products and even non-significant in industries such as Paper and Paper Products or Other Non-Metallic Mineral Products. These results are somewhat expected as it is likely that tech industries have more allowance for implementing a differentiation strategy in electronic products or electrical equipment as opposed to textiles or paper products.

These findings affirm the fact that the effect of R&D intensity is far from uniform across in-

Table 1.14: R&D and Markups : Industry-by-Industry Regression

	RDIS
13 Textiles	0.012^{**}
	(0.005)
17 Paper and Paper Products	-0.001
	(0.003)
20 Chemicals and Chemical Products	0.024^{***}
	(0.003)
22 Rubber and Plastics Products	0.013^{***}
	(0.004)
23 Other Non-Metallic Mineral Products	0.006
	(0.006)
24 Basic Metals	0.005^{**}
	(0.002)
25 Fabricated Metal Products	0.022^{***}
	(0.006)
26 Computer, Electronic and Optical Products	0.116^{***}
	(0.008)
27 Electrical Equipment	0.051^{***}
	(0.012)
28 Machinery and Equipment	0.024^{***}
	(0.004)
29 Motor Vehicles	0.029^{***}
	(0.005)
30 Other Transport Equipment	0.025^{***}
	(0.005)
31 Furniture	0.038^{**}
	(0.018)
32 Other Manufacturing	0.001
	(0.010)
33 Repair and Installation of Machinery	0.007
	(0.018)

Notes : Standard errors are reported in parentheses. * 10%, ** 5%, *** 1% level of significance.

dustries and, to make the most of R&D, it should first be examined whether there is enough capacity for increasing market power.

1.7.3 Innovation Inputs v. Innovation Outputs

It should be emphasised that the effect of R&D on markups is conditional on the assumption that R&D generates *successful* innovations that help make the firm's products differentiated from others. R&D expenditure or stock is a good measure of a firm's innovation activities[20]. However, many authors have argued that R&D is simply an innovation input (Nelson and Rosenberg, 1993), indicating that it is unclear whether investments in innovation actually lead to innovation outputs that can eventually contribute to the change in firm-level markups.

Before introducing the possible measure of the innovation output, it should first be argued that not every invention or improvement made from the R&D investments can be simply classified as innovation solely due to being *different* from the existing products or processes. Being 'different' is, according to the Oslo manual, the minimum requirement to be innovative. To qualify as innovation, it should have an additional marketability as well as practicability. These aspects have been absent in many early attempts at defining innovation. For example, Nelson and Winter (1977) defined innovation as "the wide range of variegated processes by which man's technologies evolve over time (p.37)." In addition, Schmookler (1966) had defined innovation as the action of making a technical change by which an enterprise produces new outputs or uses new inputs. In this regard, an interpretation of the term 'innovation' has long been restricted to the sole generation of new ideas. However, this overlooks the possible link between innovation and firm performances such as markups discussed in this chapter.

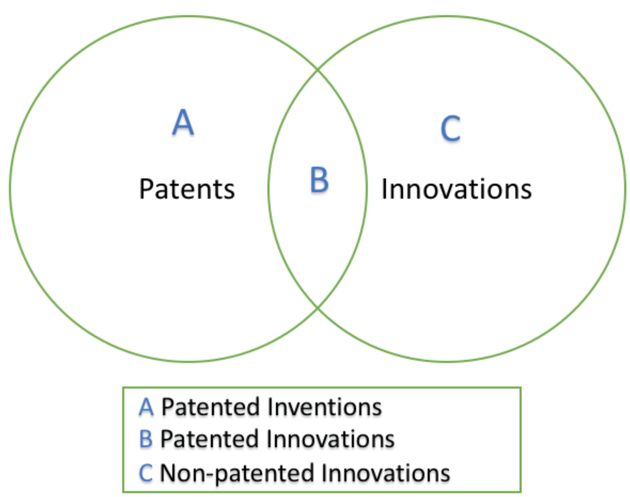
In this context, measuring the innovation output has proved to be more challenging than in the case of the input. The shortage of complete measures is usually prevalent in economics, but is particularly acute when it comes to the measurement of the innovation output. This may be attributable to its opacity (e.g. how do you define *new*? how do you measure its marketability or practicability?) and the lack of relevant firm-level data. There have been early attempts to measure the innovation output, which were based on the surveys of experts or trade journals to identify significant technical innovations that were commercialised (e.g. Acs and Audretsch, 1988; Freeman and Soete, 1997). This is a direct measure of the innovation output, as those listed on journals are more likely to be with significant commercial val-

[20]The idea of using R&D expenditure to measure innovation can be traced as far back as to the early 1930s. Godin (2002) documented that the research of M. Holland and W. Spraragen from the US National Research Council in 1933 introduced the first measure of innovation based on the amounts spent for research. However, only after the standardised definitions were established in the Frascati manual in 1963, R&D expenditure has been popularly chosen as a proxy for the innovation input. The Frascati manual is a document detailing the methodology regarding the collection of statistics about research and development, before which no standardised definition on R&D existed. It was published by the OECD first in 1963 after the meeting of the OECD experts with the NESTI (National Experts on Science and Technology Indicators) group in Frascati, Italy, hence the name of the manual. In the same year, the country-level R&D survey was conducted for the first time, with 16 participating countries (Gault, 2013)

ues. Acs and Audretsch (1988) constructed their database by screening over 100 technology, engineering and trade journals. However, this method is also not free from shortcomings. Firstly, it can be said that the number of innovations increases with the number of journals screened. Therefore, if the entirety of available journals are not screened, there is a likelihood of sample bias. Secondly, small firms are likely to be underrepresented due to potential difficulties in sustaining an appropriate journal, adding to the problem of the sample bias.

In their substitute, patent counts have often been used to proxy the innovation output (e.g. Bloom et al., 2016). This has clear merits when compared to the survey-based proxies as they are not subject to imprecise definitions of innovation. Hence, they do not suffer from the lack of comparability between firms (Ernst, 2001). However, this should still be regarded with caution. The literature has relied on the total number of patents held by firms, regardless of their practicality or marketability (e.g. Bloom et al., 2016). These patent counts, which will be denoted as the *gross patent counts* (GPC), point to the regions A and B combined in the Venn Diagram in Figure 1.3.

Figure 1.3: Venn Diagram Representing the Relationship Between Patents and Innovations



Region A, however, is associated with patents whose underlying technology is inventive, but not necessarily innovative. This invention is associated with the successful realisation of the technical requirements of an idea (Ernst, 2001), however, it does not guarantee its marketability or practicability. As regards this, Griliches (1990) noted that

“After all, a patent does represent a minimal quantum of invention that has passed both the scrutiny of the patent office as to its novelty and the test of the investment of effort and resources by the inventor and his organization into the development of this product or idea, indicating thereby the presence of a *non-negligible expectation* as to its ultimate utility and marketability (p.296)." [Italics added]

There is a marked difference between patented invention (region A) and patented innovation (region B), and such a difference is clearly manifested in the survey of the Japan Patent Office (JPO), indicating that more than 60% of patents are not considered for internal use or license-out (Nagaoka et al., 2010). If patents are not in use, it is hard to argue that they are, or at least have the potential of, contributing to firm's performances.

As briefly mentioned above, in the literature patent counts often refer to the regions A and B combined, as they are defined as the number of patents held by firms. For example, as a proxy for innovation, Bloom et al. (2016) counted only the number of patents held by firms from patents data in the electronic files of the European Patent Office (EPO). However, all patents held by firms are no more than an indicator of the successful realisation of the technical requirements, which is only a small part of innovation. Using GPC as a proxy for innovation is thus problematic, especially when innovation is defined as the successful introduction of new products into the market or new processes into actual use.

The SBA provides detailed information on patents especially. The dataset in this chapter is sufficiently rich, providing information not only on the number of patents held by a firm (GPC), but also those in actual use, denoted as the *net patent counts* (NPC). This is more representative of the region B in Figure 1.3.

Table 1.15 reports the results of the regression of markups on GPC. The variable $RDIS$ is also included because not all the demand-creating innovations from R&D are necessarily patented. Column (1), showing the result from FE, indicates that the coefficient on $RDIS$ remains positive and significant under 1% level. The magnitude of the coefficient also more or less remains equal despite the inclusion of GPC, displaying the R&D's clear role in contributing to markups. However, the coefficient on GPC is negative, despite its magnitude being negligible. The coefficient on GPC from GMM-SYS in column (2) also remains negative, however, becomes insignificant even under 10% level.

Table 1.16 presents the results from the same regressions, but with the patent variable replaced by NPC. There is no significant change seen in the coefficient on $RDIS$, whilst a change is made to the signs of the coefficients on the patent counts, as they become positive.

Table 1.15: Regression of Markups on GPC : FE and GMM

	(1) FE	(2) GMM-SYS
$L.\log\mu$		0.452^{***}
		(0.040)
GPC	-0.004^{**}	-0.053
	(0.001)	(0.016)
$RDIS$	0.024^{***}	0.044^{*}
	(0.002)	(0.023)
Industry	Yes	Yes
Year	Yes	Yes
Controls	Yes	Yes
Observation	30,552	23,880
AR(1)		0.00
AR(2)		0.26
Hansen		0.11

Note: Standard errors are reported in parentheses. ***,** and * indicate significance at 1%, 5% and 10% respectively. The Hansen test is used to test the null hypothesis that the instruments are valid. The AR test is used to find the evidence of autocorrelation in the errors.

However, they are still statistically insignificant even under 10% level. The results from Table 1.15 and 1.16 indicate that patents do not necessarily reflect the demand-enhancing innovations which are most relevant for linking innovations to firm-performances, such as profitability or markups. In this regard, NPC can be regarded as the most relevant measure in that it only counts patents actively in use. The coefficient on NPC is positive, but its magnitude is negligible and, moreover, it is not statistically significant at all.

The aforementioned results highlight the fact that not all innovations - either demand-enhancing or cost-reducing - are patented for various reasons. Although innovations are patentable and worthy of patenting, not all firms want to patent innovations with equal vigour. Many innovations made in small firms usually go unpatented due to the expense and effort which will incur over the course of an application (Romijn and Albaladejo, 2002). Also, firms may have regarded taking out a patent as inefficient as they have other means of protecting their invention, such as trade secrecy, or the pace of their technological progress may be rapid (Romijn and Albaladejo, 2002). These may explain why there are insignificant coefficients in both regressions.

Table 1.16: Regression of Markups on NPC : FE and GMM

	(1) FE	(2) GMM-SYS
$L.\log\mu$		0.581^{***}
		(0.040)
NPC	0.001	0.011
	(0.001)	(0.011)
$RDIS$	0.024^{***}	0.051^{**}
	(0.002)	(0.020)
Industry	Yes	Yes
Year	Yes	Yes
Controls	Yes	Yes
Observation	24,452	18,088
AR(1)		0.00
AR(2)		0.13
Hansen		0.20

Note: Standard errors are reported in parentheses. ***,** and * indicate significance at 1%, 5% and 10% respectively. The Hansen test is used to test the null hypothesis that the instruments are valid. The AR test is used to find the evidence of autocorrelation in the errors.

1.7.4 R&D's Effects on Marginal Costs

As briefly mentioned above, successful R&D can operate in two ways. First, it can increase prices that a firm charges by lowering price elasticity through differentiation. Second, it can reduce marginal costs by improving productivity through process innovation or better-quality intermediate inputs. It is difficult to distinguish one effect from the other, unless there is sufficient data on prices or marginal costs. This chapter assumes that successful R&D is more likely to be reflected onto price levels via lower price elasticity through differentiation.

Given the fact that a markup is the ratio of price to marginal costs and that R&D can affect marginal costs through productivity, this section attempts to control for any probable effect of R&D on markups through marginal costs by including productivity as a control variable. Therefore, the regression equation (1.13) can be re-written as follows

$$\log P_{it} - \log MC_{it} = \beta_0 + \beta_1 \log RDSI_{it} + \mathbf{X_{it}}\gamma + \beta_{\mathbf{2}}\omega_{\mathbf{it}} + \delta_{\mathbf{j}} + \delta_{\mathbf{t}} + \epsilon_{\mathbf{it}} \tag{1.15}$$

where P_{it} and MC_{it} denote prices and marginal costs of firm i at time t respectively. Also, ω_{it} denotes productivity of firm i at time t. If the inclusion of productivity is assumed to control

Table 1.17: Regression of Markups on RDIS with Productivity as Control Variable

	(1) OLS	(2) FE
$RDIS$	0.047^{***}	0.023^{***}
	(0.002)	(0.002)
Industry	Yes	Yes
Year	Yes	Yes
Controls (incd. ω_{it})	Yes	Yes
Observation	34,074	34,074

Note: Standard errors are reported in parentheses. ***,** and * indicate significance at 1%, 5% and 10% respectively.

for any change in marginal costs, the coefficient β_1 can be seen to capture the R&D's effect on price changes better. Much of the discussion will be devoted to a more fitting estimation of productivity in later chapters, but, for the current purpose, it is worth mentioning that ω_{it} is measured using the coefficient estimates for labour, capital and intermediate inputs, which were obtained in section 1.4.2[21].

Table 1.17 provides results from the regression of (1.15), with column (1) showing the results from OLS. The results show that the coefficient on $RDIS$ stands at 0.047, still statistically significant under 1% level of significance. The coefficient in the column (2) still stands at 0.023 and also remains statistically significant. The corresponding coefficients from the regressions without the productivity term have stood at 0.055 and 0.024 respectively. Subsequent to the inclusion of productivity as a control variable, these coefficients have marginally decreased to 0.047 and 0.023. This may suggest that some of the positive effects of R&D can be attributable to its effect on marginal costs through productivity, but the magnitude of such effect is not significantly large.

The results suggests that, even accounting for productivity differences, R&D plays its role in increasing firm-level markups. If productivity is assumed to control for differences in marginal costs, then the positive coefficients from Table 1.17 serve as an evidence that a firm's R&D decision is fundamentally concerned with differentiation strategy than with low cost strategy. The successful differentiation helps firms to set higher prices by lowering price elasticity of demand.

[21]Given the trans-log function is used in this chapter, ω_{it} is defined as $\hat{\omega}_{it} = q_{it} - \hat{\beta}_l l_{it} - \hat{\beta}_m m_{it} - \hat{\beta}_k k_{it} - \hat{\beta}_{ll} l_{it}^2 - \hat{\beta}_{mm} m_{it}^2 - \hat{\beta}_{kk} k_{it}^2 - \hat{\beta}_{lk} l_{it} k_{it} - \hat{\beta}_{lm} l_{it} m_{it} - \hat{\beta}_{mk} m_{it} k_{it}$, where $\hat{\beta}$ denotes the estimates for each coefficient.

1.8 Conclusion

This chapter examines the hypothesis that there is a positive association between R&D and firm-level markups. The firm-level markups are derived from the method suggested by De Loecker and Warzynski (2012), which in turn owed its insight to Hall (1988), who for the first time relied on production data in his estimation of markups. The variation in the makrups was then traced to the change in R&D and other factors such as market structure or firm size. The estimation results using fixed effcts or GMM suggest that R&D intensity significantly increases firm-level markups.

In addition, many other aspects of the R&D-markups link have been closely examined. It has been documented that there has been an increasing trend towards offshoring R&D in search of differentiated sources of knowledge and cheaper costs. The empirical results in this chapter find that the capital stock accumulated from R&D performed in-house and offhosre both significantly affects firm-level markups, however, at a varying degree. In the case of offshoring, R&D does not deliver the similarly compelling effects, possibly due to increased costs of managing far-flung operations and added complexity. In addition, the result may indicate that there is a loss in the ability to make differentiating innovations if the firm's core innovation activities, such as R&D, are offshored and the firm relies on foreign supply of technologies. This may be all the more relevant in the age of rapidly evolving consumer preferences in domestic markets. Also, even though R&D is shown to be markup-enhancing, it has been found that the effect does not uniformly apply across all industries. The results show that there are striking variations in the degree of effect from one industry to another.

As part of a robustness check, patent counts have also been included to account for the fact that R&D investments are merely innovation inputs rather than outputs. Despite the inclusion of the patent counts, there were no changes in the effect of R&D intensity on markups and, moreover, there were no significant effects found from the patent counts variable. This provides a couple of implications. Firstly, patents are not likely to be the best measure for the innovation output. Secondly, not all innovations related to demand-enhancement are likely to be patented for the various reasons mentioned above.

The main conclusion in this chapter is that the positive link between R&D and productivity, that has been established in the related literature, can be partially attributable to the change in markups rather than efficiency as the term 'productivity' is often understood in the literature. In this regard, these findings highlight the largely overlooked functions of R&D, not only as a contributor to technology and productivity growth, but also as a booster of demand through identifying and materialising unique selling points that will differentiate their products from others.

Chapter 2

Trade and Real Productivity : Evidence from Korean Manufacturing Industry

2.1 Introduction

One of the established empirical facts in the literature is that exporting firms are noticeably different from firms that only serve the domestic market. Beginning with Bernard et al. (1995), a large volume of literature has documented that exporting firms are likely to be more productive than non-exporting ones (e.g. Baldwin and Gu, 2003; Wagner, 2007).

Two possible mechanisms have been suggested in a number of recent studies to explain these differences between exporting and non-exporting firms. Firstly, it has been suggested that there is a self-selection of high productive firms into export markets (self-selection hypothesis). Participation in the export markets usually involves a range of fixed costs that low productivity firms cannot afford (Melitz, 2003). Secondly, exporters become more productive after exporting through various channels (learning-by-exporting hypothesis)[1].

[1]There are many theoretical models which have outlined a variety of mechanisms through which exporters become more productive after exporting. They mainly focus on technology spillovers from leading countries to countries with lower productivity (e.g. Grossman and Elhanan, 1991; Ben-David, 2000). This hypothesis is, to a certain degree, supported by the absence of learning-by-exporting effects in advanced countries such as the United States or the United Kingdom (e.g. Bernard and Jensen, 1999; Greenaway and Kneller, 2004) and its presence in developing countries such as China or Vietnam (e.g. Kraay, 1999; Newman et al., 2017). However, Fryges and Wagner (2008) also found evidence for learning-by-exporting with the German data. Feeney (1999) opened a possibility that even firms in advanced countries can benefit from exporting experience because it

Many researchers have attempted to answer 'the chicken or the egg' causality question. As Table 2.1 indicates, many different datasets have been examined using various econometric techniques. All the authors listed in Table 2.1 found that there is evidence for self-selection into export markets. However, relatively more recent researches by Baldwin and Gu (2003), Yasar and Rejesus (2005), De Loecker (2007), Fryges and Wagner (2008) and Newman et al. (2017) found evidence for learning-by-exporting, which had been considered insignificant in the early literatures (Wagner, 2007).

This chapter attempts to answer the perpetual 'chicken or egg' question by using a firm-level data on Korean manufacturing that covers the period between 2006 and 2015. Korea is an interesting country not only due to its high dependency on exports as a result of its relatively small domestic market, but also due to its high level of absorptive capacity in exploiting learning-by-doing opportunities. The data shows that each year, on average, 64% of the manufacturing firms are exporters and approximately 4.5% of them decide to implement exporting.

Rather than being a mere addition to the existing literature with the Korean dataset, this chapter contributes to the long-running debate on 'the chicken or the egg' causality dilemma by providing a new perspective. This difference in perspective is brought about by placing more emphasis on the better measurement of productivity. This can be seen as a natural question to start with, but has been given little attention in the relevant literature.

Table 2.2 shows the productivity measures that have been used in the current existing literature. Clerides et al. (1998) used the average variable costs and their reduction as an indication of an increase in productivity. Rich in information, the databases they used contained information on inputs, outputs and costs. However, it has proved difficult to obtain this firm-level data on costs. Fryges and Wagner (2008) and Newman et al. (2017) instead used labour productivity as the measure of productivity. This simple measure has limitations as changes in labour productivity may simply reflect the substitution of other factors for labour (Houseman, 2007)[2].

allows them to experience learning-by-doing by specialisation due to trade. Moreover, Bloom et al. (2016) suggested that productivity can even increase as a result of intensifying competition from foreign producers.

[2]Theoretically, the level of efficiency or intensity with which inputs are used to produce an output can be simply measured as the output-input ratio. In this regard, labour productivity, units of output per labour hour, is one of the most widely used measures of productivity. However, labour productivity has a shortcoming in that it is also affected by the excluded factors such as capital. For example, even though two firms have exactly the same technology, they can end up having different labour productivity, when one of them uses more capital than the other. Then, labour productivity itself is a misleading measure of the firm's efficiency, "if one happens to use capital much more intensively, say because they face different factor prices (Syverson, 2011, p.330)."

Table 2.1: Literature Review (i)

	Dataset	Self-selection	Learning-by-exporting
Clerides et al. (1998)	Colombia, Mexico, Morocco	✓	×
Kraay (1999)	China	✓	✓
Bernard and Jensen (1999)	U.S.	✓	×
Aw et al. (2000)	Korea, Taiwan	✓	×
Delgado et al. (2002)	Spain	✓	×
Baldwin and Gu (2003)	Canada	✓	✓
Greenaway and Kneller (2004)	United Kingdom	✓	×
Yasar and Rejesus (2005)	Turkey	✓	✓
De Loecker (2007)	Slovenia	✓	✓
Fryges and Wagner (2008)	Germany	✓	✓
Newman et al. (2017)	Vietnam	✓	✓

The most frequently used measure in the existing literature is total factor productivity (TFP). The methods of estimating TFP - index or semi-parametric approach - have been well established that some authors now disregard the need for describing their methods to estimate it (e.g. Baldwin and Gu, 2003; Greenaway and Kneller, 2004). De Loecker (2007) made one of the few attempts to modify the established semi-parametric (Olley-Pakes) method to place the estimation in the context of export markets. However, it still remains true that, regardless of the methods employed, they all identify residuals with firm-level productivity.

It is argued in this chapter that the use of TFPs, as obtained from the existing methods, can be problematic. The residual-based TFPs not only portray efficiency, but also measurement errors or unexpected transitory shocks that are hardly related to the theoretical grounds provided in the existing literature. Thus, real TFP is suggested in this chapter whose description will be provided in detail in the next section. In short, the real TFP is a productivity in which measurement errors or transitory productivity shocks are netted out.

The existing literature has given little attention to the measurement of TFPs, using residuals as its measure. A state-space model can be used to separate out real productivity from "a true measure of our ignorance" (Fuentes and Morales, 2011, p.157). However, its appli-

Table 2.2: Literature Review (ii)

	Productivity Measure
Clerides et al. (1998)	Average Variable Costs
Bernard and Jensen (1999)	TFP (Olley-Pakes)
Aw et al. (2000)	TFP (Index)
Delgado et al. (2002)	TFP (Index)
Baldwin and Gu (2003)	TFP
Greenaway and Kneller (2004)	TFP
Yasar and Rejesus (2005)	TFP (Olley-Pakes)
De Loecker (2007)	TFP (Olley-Pakes)
De Loecker (2013)	TFP (Olley-Pakes)
Fryges and Wagner (2008)	Labour Productivity
Newman et al. (2017)	Labour Productivity

cation is computationally challenging. This chapter suggests a relatively simpler method to measure real productivity by using the semi-parametric estimation of production functions.

The present chapter finds evidence for the learning-by-exporting effect in the Korean manufacturing sector. More importantly, it is found that two different measures of productivity paint starkly different pictures of productivity trajectories before and after the decision to implement exporting. To my knowledge, this is one of the first attempts to investigate the link between export and productivity with a suggestion of alternative measures other than labour productivity or TFP (see Table 2.2).

Moreover, as part of the robustness check, this chapter also investigates the relationship between markups and exporting. This is to account for the fact that, due to limited data availability, productivity is measured using sales rather than quantity variable. Therefore, an increase in productivity is possibly due to either of the two effects : technical efficiency or demand change. As there is no sufficiently detailed data on firm-level prices and quantity, it is difficult to isolate one effect from the other. However, the investigation into the link between markups and exporting helps to indirectly measure the magnitude of the latter effect. The finding shows no evidence of the link between markups and exporting, thus lending further weight to the productivity-enhancing effects.

This is related to the works of De Loecker (2007) or De Loecker (2013) in which modifying the well-established semi-parametric methods such as the Olley-Pakes and Levinsohn-Petrin methods were attempted. In the resulting analysis of the effect of export on productivity, De Loecker paid extra attention on the correct measurement of productivity in the spirit of Olley and Pakes (1996). Building on De Loecker's ideas, the measure suggested in this chapter is a simple derivative from the modified Levinsohn-Petrin estimation algorithm. However, it is consistent with the notion of productivity according to existing literature on export and productivity.

The chapter is organised as follows; Section 2.2 introduces the concept and estimation of real total factor productivity, with section 2.3 providing brief description of the data used in this chapter. In section 2.4, empirical strategies for this chapter are provided and the results, with their interpretations introduced in section 2.5. Finally, Section 2.6 provides an investigation into markups and exporting as part of robustness check and the last section concludes the chapter.

2.2 On Real Total Factor Productivity

2.2.1 Definition of Real Total Factor Productivity

Obtaining TFP estimates at the micro-level[3] is predicated on consistent estimates of the production function. With firm-level analysis, the major econometric issue regarding the estimation of the production function is that there is a productivity shock which is observed by the firm and determines the level of observed inputs, but is unobserved by the econometrician (Marschak and Andrews, 1944). To avoid endogeneity arising from the unobserved productivity shock[4], instrumental variables and fixed effects estimation (Mundlak, 1961)

[3]There has recently been a surge in interest in productivity analysis at the micro-level. There are a couple of reasons to explain this increased interest in micro-level TFP. Firstly, it is mainly attributable to the growing availability of the firm or plant level data. Secondly, it is also attributable to the theoretical shift from competitive to non-competitive models which focus on increasing-returns to scale, non-competitive markets, externalities and Schumpeterian creative destruction process (Del Gatto et al., 2011). In these models, productivity is a micro-level productivity, which in turn is an endogenous response to micro-level policy. The host of interesting questions arising from the models therefore necessitates micro-level productivity (Bartelsman and Doms, 2000), which enables the "level of resolution unattainable with aggregated data" (Syverson, 2011, p.327).

[4]The bias induced from this unobserved productivity shock has been termed *simultaneity bias* in the literature. It is also called "transmission bias" (Griliches and Regev, 1995)

were suggested early on, but, for one reason or another[5], they have not been particularly successful at overcoming these endogeneity issues (Ackerberg et al., 2006).

In the continued search, proxy-variable approach[6] by Olley and Pakes (1996) and Levinsohn and Petrin (2003) has since gained popularity in the literature[7]. Their main contribution was showing that one can invert input demand functions to " essentially allow an econometrician to observe unobserved productivity shocks (Ackerberg et al., 2015, p.2412)" under a certain set of assumptions. Olley and Pakes (1996) suggest using a firm's investment function as a proxy for unobserved productivity shocks, whereas Levinsohn and Petrin (2003) used an intermediate inputs function rather than investment as a proxy due to lumpy characteristics of investments. Since then, there have been incremental refinements to estimation procedures. For example, Ackerberg et al. (2015) extended the aforementioned semi-parametric methods and solved the identification issue with the labour coefficient due to multi-collinearity[8]. Wooldridge (2009) suggested a one-step system GMM approach which enables the estimation of robust standard errors, delivering higher efficiency compared to the two-step semiparametric procedures.

Each estimation procedure differs depending on its own valid set of assumptions, however, they concomitantly share the same threads in that all procedures focus on the identification of consistent production function estimates and identify the resulting residuals with productivity. This, however, may cause problems in the literature in terms of the produc-

[5]Input prices can be suggested as instrumental variables as long as they are observable and not correlated with productivity shocks. However, firm-level input prices are not easily obtainable. Moreover, if firms operate in the same output and input markets, and use the same inputs, then it is hard to expect any cross-sectional variations in the firm-level input prices. Even if they operate in different input markets, observed cross-sectional variation can be correlated with the unobserved productivity shocks of a firm, making input prices invalid instruments (Aguirregabiria, 2009). Moreover, fixed-effects estimators often generate unreasonably small (or negative) estimates of capital. Firstly, it is a strong assumption that unobserved productivity stays constant, especially when one deals with long periods of time. Secondly, the bias due to measurement errors is exacerbated when taking within-estimator transformation, given that input variables, especially capital, are persistent and measurement error is not serially correlated. The transformation reduces the signal and increase the noise, hence worsening the signal-noise ratio. As regards this, Collard-Wexler and Loecker (2016) suggested that the fact that there is no variation left in the time series of capital implies that a change in capital is contaminated by measurement error.

[6]Proxy-variable approach represented by the Olley-Pakes or Levinsohn-Petrin method is not the one and only strand in the estimation of production functions. There is another strand of the dynamic panel approach of Arellano and Bond (1991), Arellano and Bover (1995) and Blundell and Bond (2000). They relax the strong assumption of fixed unobserved productivity and allow it to vary across time.

[7]In the footnote of Ackerberg et al. (2006), they noted that there were 598 cites of Olley and Pakes (1996) and 219 cites of Levinsohn and Petrin (2003) according to their search from Google Scholars. However, as of March 2018, the corresponding numbers have increased to 5152 and 4137 respectively, demonstrating their constant, and even growing, popularity in the empirical literature.

[8]See Appendix A.1 for more detail.

tivity effects of various policy measures[9]. There can be a mismatch between the theoretical grounds the literature puts forth and the actual measure of productivity it employs. Javorcik (2004) investigated the effects of FDI on productivity, which theoretically is expected to bring about new technologies and management skills. Amiti and Konings (2007) examined the effects of imported inputs on productivity via transfer of technology embodied in imported inputs. Bloom et al. (2016) examined the effects of Chinese import competition on productivity through adoption of new technologies and innovation. The issue in these studies is that the measure of TFP that was employed for empirical estimation was a Solow-type residual from the semi-parametric production function estimation. The resulting residual, however, has a likelihood of contamination from transitory shocks or measurement errors. This indicates that the positive correlation that the studies find between policy and productivity may in fact be reflecting the correlation between policy and 'non-real' productivity.

From a purely statistical point of view, TFP is nothing but a residual of the production function estimation. As with all residuals, it is understood as a catch-all for anything that engenders a shift in the production function (Solow, 1957). In some ways, it is merely a measure of our ignorance (Abramovitz, 1956). Thus, it takes a leap of faith to equate the residual with the firm's productivity, which is determined by its efficiency. The level of TFP, measured as a residual, will contain information on not only the level of technology or managerial ability that is directly related to the firm's efficiency or intensity, but also measurement errors or transitory productivity shocks, which is neither innate nor controlled by the firm's management. When it comes to measuring the *growth* of productivity, one is interested in tracing the change in the former, rather than the latter components.

This chapter suggests the econometric derivation of 'real TFP'. By real TFP, the term refers to a firm's productivity that is 1) relevant for firm's *persistent* technical efficiency or managerial ability, 2) not influenced by measurement errors or unexpected transitory productivity shocks. The real TFP thus defined has distinctive features. Firstly, it is observable by the firm, because it includes innate managerial ability as well as expected downtime, due to machine breakdowns or planned repairs and estimated defect rates. After having full knowledge on this observable productivity, the firm can decide on the level of inputs to employ. Secondly, it can be controlled and improved by the firm's innovation or management policy. Training of managers, reallocation of firm resources towards more efficient use or technology diffusion from imported materials will contribute to the improvement of real productivity.

[9]Offshoring (Amiti and Wei, 2009; Hijzen et al., 2010; **?**), exporting (Wagner, 2007), importing (Amiti and Konings, 2007; Kasahara and Rodrigue, 2008; Halpern et al., 2015), foreign direct investment (Haskel et al., 2007; Javorcik, 2004), R&D investments (Griliches, 1988). The list is not exhaustive.

2.2.2 Estimation of Real Total Factor Productivity

Suppose a simple Cobb-Douglas function

$$Y_{it} = A_{it} K_{it}^{\beta_k} L_{it}^{\beta_l} \tag{2.1}$$

where Y_{it} denotes real[10] value-added of firm i at time t and K_{it} and L_{it} denote capital and labour of firm i at time t respectively. A_{it} denotes the measure of the level of TFP of firm i at time t, which is unobservable to the econometrician. Taking logs on equation (2.1),

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \epsilon_{it} \tag{2.2}$$

where variables in (natural) logs are written in lower case and $\ln A_{it} = \beta_0 + \epsilon_{it}$. Subsequently, the residual (plus constant) is used as the measure of the level of firm-level total factor productivity (TFP_{it}).

$$TFP_{it} = \hat{\epsilon}_{it} + \hat{\beta}_0 = y_{it} - \hat{\beta}_l l_{it} - \hat{\beta}_k k_{it} \tag{2.3}$$

where $\hat{\beta}_l$ and $\hat{\beta}_k$ denote the consistent estimators of β_l and β_k respectively. In the existing literature, any shift in TFP has been considered as (Hicks-neutral) technological change or managerial ability. However, there is reason to doubt that TFP is an exact measure of these.

Basic Setup

The semi-parametric estimation algorithm not only aids to circumvent the econometric issues - simultaneity or selection bias - but also provides a way to purge the productivity measure of transitory productivity shocks or measurement errors that are likely to be unrelated to the firm's long-term underlying productivity. For this purpose, the following specification is employed

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \omega_{it} + \eta_{it} \tag{2.4}$$

[10] In the theory of production, Y_{it} reflect physical quantities of output. However, in practice, it is hard to avail oneself of the data on physical quantities. Revenues are observed more often than not. Using revenues as a measure of firm-level productivity can be problematic because price variations across firms may reflect their market power, instead of firm's efficiency. Thus, it is necessary to deflate it using an appropriate price-index to net out a change in prices. It may be more desirable if the price index also takes quality differences into account (Syverson, 2011). This issue will be dealt more in detail in the later section.

where ω_{it} denotes a part of TFP[11] observable to the firm prior to making decisions on inputs at time t. This captures an innate ability, natural endowment, as well as the level of technology, including managerial ability, expected downtime due to machine breakdowns or repairs or estimated defect rates. In other words, ω_{it} constitutes an underlying productivity of a firm, which can be observed to a certain degree and even be improved upon by an intentional act by the firm.

On the other hand, η_{it} denotes an error term unknown to both firm and econometrician prior to making decisions at time t. Whilst ω_{it} represents the management controlled portion in the measure of the level of TFP, η_{it} represents measurement errors in the output variable or any unpredictable deviation from estimated managerial ability, expected downtime or estimated defect rates. The latter, especially measurement errors, do not necessarily constitute an underlying productivity of a firm, which will obscure the comparison of productivities of the firm between two different points in time.

As the identification strategy is mainly based on the Olley-Pakes (OP) and Levinsohn-Petrin (LP) methods, the following assumptions are assumed to be satisfied (see Appendix B.1 for the brief description OP method).

Assumption 1 (First Order Markov Process)

$$\omega_{it+1} = E[\omega_{it+1}|\omega_{it}] = g(\omega_{it}) + \zeta_{it+1} \tag{2.5}$$

The assumption states that ω_{it+1} evolves according to an exogenous first order Markov process. That is, actual productivity ω_{it+1} consists of expected productivity $g(\omega_{it})$ and a productivity innovation ζ_{it+1}[12]. At time t, firms are assumed to observe ω_{it}, but do not know future ω's other than their conditional probability distributions.

The productivity innovation ζ_{it+1}, mean independent of ω_{it} by construction, represents the uncertainties inherently linked to productivity (Doraszelski and Jaumandreu, 2013) and captures the factors that have a persistent impact on productivity such as improvement in management or an absorption of new technologies. Such factors can be the outcomes of the

[11] In the existing literature, ω_{it} is often referred to as TFP (e.g. Aguirregabiria, 2009). However, strictly speaking, TFP^s refers to $\beta_0 + \omega_{it} + \eta_{it}$ in the sense that they increase the marginal productivity of all factors simultaneously.

[12] It can be expressed that productivity is governed by a first-order Markov process with transition probabilities $P(\omega_{it+1}|I_{it}) = P(\omega_{it+1}|\omega_{it})$, where I_{it} is the information set at time t and $P(\cdot)$ is the distribution. The firm knows about the distribution of the productivity and it stochastically increases in ω_{it}.

intentional management policy such as exports or imports (Keller, 2004; Amiti and Konings, 2007; De Loecker, 2013; Halpern et al., 2015), R&D investments (Griliches, 1988) or offshoring (Amiti and Wei, 2009; Hijzen et al., 2010).

Assumption 2 (Dynamic and Non-dynamic Inputs)

Capital k_{it} is determined according to

$$k_{it} = f(k_{it-1}, i_{it-1})$$

where i_{it-1} denotes an investment made in period $t-1$. This renders k_{it} a dynamic input whereas labour l_{it} is a non-dynamic input chosen at time t. Intuitively, it takes a full production period for new capital to be ordered, delivered and installed and the assumption is necessary for generating the moment conditions for estimation (Ackerberg et al., 2015).

Assumption 3 (Scalar Unobservable)

$$m_{it} = m_t(k_{it}, \omega_{it}, EXP_{it}) \tag{2.6}$$

where $m_t(\cdot)$ is a non-parametric function of two state variables k_{it} and ω_{it}[13]. The assumption states that ω_{it} is the *only* unobservable scalar in the intermediate input function[14]. This prevents ω_{it} from following higher than a first order Markov process (Ackerberg et al., 2007). This assumption is important as it implies that the level of demand for intermediate inputs contains information on the level of productivity, which is of main interest. This productivity, which is observable to the firm and not to the econometricians, is based on the plausible assumption that they have a good knowledge of their productive capacity. Even though there can be deviation due to unexpected disruptions, breakdowns or simple measurement errors, these are not part of the productivity that this chapter is interested in.

[13]It is worth noting that m_t is indexed by t that allows intermediate inputs demand function to vary according to demand conditions or industry structure that are assumed to be constant across firms. This represents restrictions, for example, that firms operate in the same labour and intermediate input markets and in the same output market with homogenous goods or completely symmetric product differentiation (Ackerberg et al., 2015). This implies that two firms with the same k_{it} and m_{it} do not necessarily have the same ω_{it} if they operate in different time periods.

[14]This assumption implies that there can be no measurement error in the intermediate inputs function or no unobserved factors that affect intermediate inputs not production. This is a fairly strong assumption, but it is crucial to ensure that productivity ω_{it} is expressed in terms of observables.

EXP_{it} represents the exporter status variable of firm i at time t. It is assuemd that exporting firms face different market structures and factor prices when they make decisions regarding intermediate inputs. This assumption is accounted for by including the exporter status variable in $m_t(\cdot)$ as in Van Biesebroeck (2007) and De Loecker (2007).

Assumption 4 (Strict Monotonicity)

$$m_t(k_{it},\omega_{it},EXP_{it}) \text{ is strictly increasing in } \omega_{it}$$

The strict monotonicity assumption states that the demand for intermediate inputs strictly increases in productivity that is conditional on other state variables. Along with the scalar unobservable assumption, it ensures the invertibility of the intermediate input function[15].

First Stage

In the estimation of equation (2.4), the firm with this prior knowledge regarding ω_{it} will determine the level of inputs based on its level observable at time t. This renders the input variables no longer exogenous (Marschak and Andrews, 1944). The resulting OLS coefficients are likely to be biased as they get to capture the effect of ω_{it} on output. Levinsohn and Petrin (2003) provided a solution to avoid this so-called simultaneity bias by using intermediate inputs[16] as a proxy to control for ω_{it}. Consequently, the assumptions of scalar unobservable and strict monotonicity ensure that equation (2.6) can be expressed as below

[15] Refer to Pakes (1991) for the proof that *investment* is monotonic in productivity. As it invovles the firm's dynamic problem, this can be computationally challenging as Pakes demonstrates (Levinsohn and Petrin, 2003). The main idea is that, if it is assumed that $P(\omega_{it+1}|\omega_{it})$ stochastically increases in ω_{it}, an increase in ω_{it} will positively impact the distribution of all future productivity. Then, the marginal product of capital at period $t+\tau$ will be positively impacted by the level of productivity at $t+\tau$. Thus, there will be an increase in current investment demand at t.

[16] Olley and Pakes (1996) use an investment as a proxy, but the use of intermediate inputs has two obvious benefits as emphasised by Levinsohn and Petrin (2003). Firstly, firms almost always report intermediate inputs such as materials or electricity. This enables one to avoid truncating firms with zero investment due to non-invertibility. The microdata confirms that investment is lumpy in the sense that there is zero investment for most of the periods and sporadic periods of large investments (Petrin et al., 2004). Being explained by the existence of non-convex adjustment costs (fixed or kinked costs), the 'lumpiness' implies that plants' demand for investment may not fully respond to productivity shocks. Secondly, because intermediate inputs are not state variables, it provides a simple link between the economic theory and the estimation strategy. Ackerberg et al. (2015) note that, as intermediate inputs are non-dynamic inputs, it is easier to verify the assumption that the intermediate inputs function is strictly increasing in productivity in comparison to another that the investment function is.

$$\omega_{it} = m_t^{-1}(k_{it}, m_{it}, EXP_{it}) = j_t(k_{it}, m_{it}, EXP_{it}) \tag{2.7}$$

Equation (2.7) implies that the productivity ω_{it} is a function of k_{it}, m_{it} and EXP_{it} whose exact functional form is unknown. Then, equation (2.4) can be re-expressed as

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + j_t(k_{it}, m_{it}, EXP_{it}) + \eta_{it} \tag{2.8}$$

Using $\Phi_t(\cdot) \equiv \beta_0 + \beta_k k_{it} + \beta_m m_{it} + j_t(k_{it}, m_{it}, EXP_{it})$,

$$y_{it} = \beta_l l_{it} + \Phi_t(k_{it}, m_{it}, EXP_{it}) + \eta_{it} \tag{2.9}$$

Equation (2.9) is the partially linear model where the the parametric part is given by β_l, whilst the non-parametric part is the unknown function $\Phi_t(k_{it}, m_{it}, EXP_{it})$. Consequently, this partially linear equation can be estimated using Robinson (1988)'s double residual methodology through which consistent estimators of the coefficient β_l and $\Phi_t(\cdot)$, which will be denoted as $\hat{\beta}_l$ and $\hat{\Phi}_t(\cdot)$ respectively, can be obtained.

$$\hat{\eta}_{it} = y_{it} - \hat{\beta}_l l_{it} - \hat{\Phi}_t(k_{it}, m_{it}, EXP_{it}) \tag{2.10}$$

where $\hat{\eta}_{it}$ denotes the residual from equation (2.9).

Second Stage

Using the assumption of first-order Markov process, equation (2.4) can be re-expressed as

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_k k_{it} + g(\omega_{it-1}) + \zeta_{it} + \eta_{it} \tag{2.11}$$

As capital is dynamic by assumption, k_{it} does not respond to innovation shocks at time t. This provides the following moment as below

$$E[\zeta_{it} + \eta_{it} | k_{it}] = 0 \tag{2.12}$$

which will enable the identification of β_k. Given the guesses of β_k, which is β_k^*, and the consistent estimator of β_l from the first stage, the residual $\widehat{\zeta_{it} + \eta_{it}}$ can be obtained as below

$$\hat{\zeta_{it}+\eta_{it}}(\beta_k^*) = y_{it} - \hat{\beta}_l l_{it} - \beta_k^* k_{it} - g(\hat{\omega_{it-1}}) \tag{2.13}$$

where $\hat{\zeta_{it}+\eta_{it}}(\beta_k^*)$ denotes the residual from the estimation of (2.11) given β_k^*[17]. Starting with the guesses, the task now is to find the estimator $\hat{\beta}_k$ which will make the sample analogue of the population moments approximately equal to zero. $g(\hat{\omega_{it-1}})$ can be obtained by non-parametrically estimating the following equation

$$\omega_{it} = g(\omega_{it-1}) + \zeta_{it} \tag{2.14}$$

To estimate this, with the consistent estimator $\hat{\Phi}_t$ from the first stage, the following implied productivity is constructed

$$\hat{\omega}_{it}(\beta_k^*) = \hat{\Phi}_t - \beta_k^* k_{it} \tag{2.15}$$

The implied productivity $\hat{\omega}_{it}(\beta_k^*)$ will be consistent if the guesses are also consistent. Subsequently, $g(\omega_{it-1})$ is represented non-parametrically using a polynomial in $\hat{\omega}_{it}(\beta_k^*)$. This establishes $\hat{\zeta_{it}+\eta_{it}}(\beta_k^*)$, which in turn enables the construction of the following GMM criterion

$$Q(\beta_k^*) = \min_{\beta_k^*} \sum_{i=1}^{N} \sum_{t=1}^{T} (\zeta_{it} \hat{+} \eta_{it}(\beta_k^*) k_{i,t})^2 \tag{2.16}$$

and the solution to the above minimisation process will provide fa consistent estimate $\hat{\beta}_k$[18].

Third Stage

Suppose the consistent estimators for β_l and β_k are obtained. Given these consistent estimators, $\hat{\omega}_{it}$ is an asymptotically consistent estimator of ω_{it}, which is expressed as

$$\hat{\omega}_{it} = \hat{\Phi}_i(\cdot) - \hat{\beta}_k k_{it}$$

[17] The coefficients from the OLS estimation of equation (2.2) were used as the guesses.

[18] Additional moments such as

$$E[\zeta_{it} + \eta_{it} | l_{it-1}] = 0 \quad E[\zeta_{it} + \eta_{it} | k_{it-1}] = 0 \tag{2.17}$$

can be used to improve efficiency (Petrin et al., 2004).

where $\hat{\beta}_k$ denotes the consistent estimators of β_k. As this productivity does not include η_{it} any longer, it has been denoted as the real total factor productivity ($RTFP$) as follows

$$RTFP_{it} = \hat{\omega}_{it} = \hat{\Phi}_t - \hat{\beta}_k k_{it} = \tilde{y}_{it} - \hat{\beta}_l l_{it} - \hat{\beta}_k k_{it} \tag{2.18}$$

where $\tilde{y}_{it}$ denotes predicted values from the estimation of equation (2.9). This differs from the usual TFP which is normally used in the existing literature (e.g. Olley and Pakes, 1996; Levinsohn and Petrin, 2003) as the latter includes the effects from transitory shocks, η_{it} as below

$$TFP_{it} = \widehat{\omega_{it} + \eta_{it}} = y_{it} - \hat{\beta}_l l_{it} - \hat{\beta}_k k_{it} \tag{2.19}$$

However, this chapter argues that the real total factor productivity resonates better with the concept of productivity, which is essentially about efficiency and technological change.

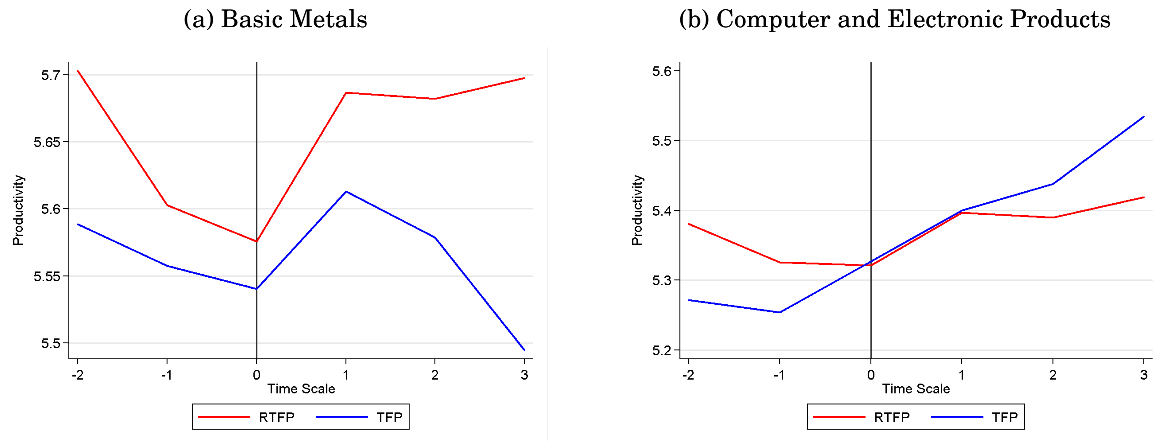
2.2.3 Comparison of RTFP and TFP

Before moving on, a graphical framework is presented to show the intuition behind the necessity of RTFP. Figure 2.1 shows the productivity trajectories of firms entering export markets. The time scale on the horizontal axis denotes zero as the point in time when firms begin exporting, shown by the vertical reference line. It should be noted that this is not the comparison of productivity between export starters and non-exporters, which is eventually needed to examine the learning-by-exporting hypothesis. The figure shows how average productivity of export starters pans out before and after the decision to export with two different measures, RTFP and TFP.

Figure 2.1 (a) indicates that there is a sharp increase in productivity after the decision to export, providing some evidence of the learning-by-exporting in the Basic Metals industry. An increasing trend is found regardless of the productivity measures, at least during the first year from the decision to export. The higher productivity is somewhat maintained once RTFP is employed in later years. However, the learning-by-exporting effect becomes short-lived and the increasing trend is dramatically reversed in later years when TFP is employed. The trajectory, shown in solid blue, delivers an impression of random walks, which constantly shifts up and down, at least during the time period considered.

Similarly, Figure 2.1 (b) also seems to support the presence of learning-by-exporting in the

Figure 2.1: RTFP and TFP comparison : Basic Metals and Computer and Electronic Products



Computer and Electronics Products industry. Subsequent to exporting, firms experience an increase in productivity. However, the two measures paint somewhat different pictures of productivity trajectory. When TFP is employed, there is a constant increase in productivity even before the decision to export. This increasing trend continues, at a similar rate, after the firms start exporting. However, when RTFP is employed, productivity somewhat flattens before firms commence exports. Following the decision to export, there is some evidence of learning-by-exporting in subsequent years, but at a much less dramatic rate.

The comparison is made here to stress the point that RTFP and TFP are intended to portray different aspects. This chapter does not argue for precedence of one measure over the other. However, when the aim is to investigate the link between export and productivity, it can be that that RTFP better suits the purpose as it is more directly related to a firm's efficiency, which is often held up as the essence of theoretical link. Moreover, this does not necessarily constitute the unambiguous evidence of learning-by-exporting as it is no more than visual inspection that does not establish causal relationship between export and productivity. More rigorous empirical strategies will be provided in section 2.4.

2.3 Data and Descriptive Statistics

2.3.1 Data: Survey of Business Activities

This chapter is based on a firm-level database, which in turn is based on the annual Survey of Business Activities (SBA) collected by Statistics Korea (KOSTAT). The dataset is an

Table 2.3: Summary Statistics (i)

	Average (2008 - 2013)
(1) Number of Starters	173
(2) Number of Exporters	3212
(3) Number of Firms	5010
(1)/(2)	5.3%
(2)/(3)	64.1%

unbalanced panel of all enterprises with at least 50 employees or 300 million won capital in the period of 2006 to 2015. The dataset contains rich information on sales, employees, capital, intermediate inputs, wages as well as various firm-level characteristics such as foreign ownership, export or import activity and the number of patents.

The data on firms' export activity helps to establish the causal relationship by differentiating between export starters and firms that only serve the domestic market. Export starters are defined to be firms that export in year t (at least for two consecutive years) and had never exported in previous years, at least in years $t-1$ and $t-2$[19]. Export starters will be compared with those with no experience of exporting, and which serve the domestic market only. They are denoted as non-exporters[20].

2.3.2 Descriptive Statistics

Table 2.3 summarises the exporting status of the Korean manufacturing firms between the years of 2008 and 2013[21]. According to the table, the average number of firms is 5010, whilst the average number of exporting firms is 3212. This represents a significant share of 64.1%, which indicates a high dependency on exports of the Korean manufacturing firms. The first row in the table indicates that the average number of export starters is 173, which only accounts for 5.3% of the exporters[22].

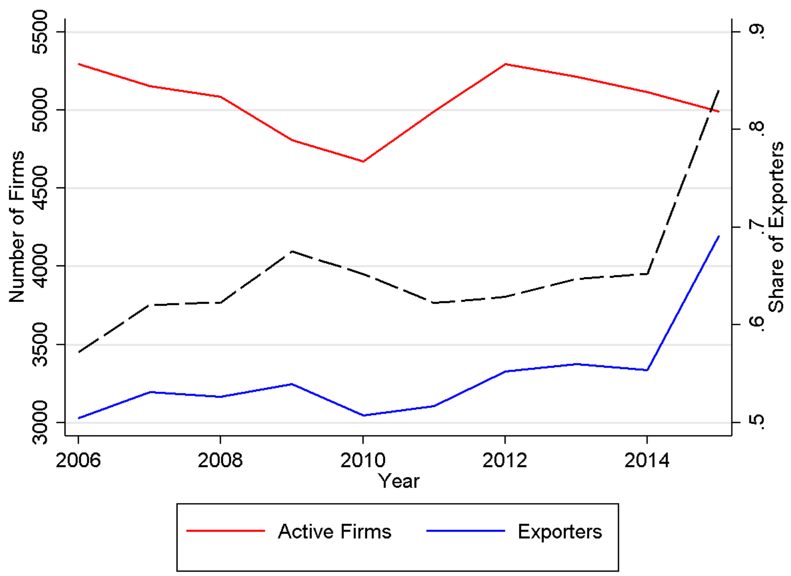
[19]After the entry, one-year exit is allowed, but if the exit lasts for more than one period, then it is considered to stop exporting.

[20]Additionally, firms that report a positive amount of exports in year t and in year $t-1$ and $t-2$ are defined as continuers, whereas those with zero export in years $t+1$ and t and a positive amount of exports in year $t-1$ as stoppers

[21]The survey data covers the period from 2006 to 2015, but the summary statistics in Table 2.3 are only available from 2008 to 2013. This is related to the way the variables are defined. For example, to be classified as export starters, it was requested that the firms report any amount of exports during the previous two years and, after the entry, report positive exports at least for two consecutive years.

[22]During the sample period, 1042 firms have entered the export market at different points in time. These export starters will be compared with non-exporters to investigate the effects of export decisions on firm-level productivity

Figure 2.2: Share of Exporters over Time



Note : The dotted line represents the share of exporters which is the ratio of the number of exporters to that of active firms.

Figure 2.2 shows the change in the share of exporters over time between 2006 and 2015. The share, represented by the dotted line, begins at 57.2% in 2006 and has shown a gradually increasing trend, even showing a marked rise in the share in 2015, amounting to a staggering 84.0%. However, caution needs to be exercised when interpreting the results, as the change in the share can also be brought about by the change in the number of active firms, which has continually decreased since 2012.

The annual average of exporter share is relatively high on the whole in Korean manufacturing[23], but it is worth noting that there is still a wide variation in the shares across the industries. Table 2.4 demonstrates that the shares are markedly high in medium-high technology sectors[24] such as electrical equipment (79.8%), chemical products (79.1%) and motor vehicles (75.1%). However, the same figures are somewhat predictably low in low technology sectors such as paper products (52.1%), wearing apparel (47.0%) and non-metallic mineral products (42.3%) such as glass, cement or lime. This shows that technology-intensive manufacturing firms operating in Korea are relatively more export-intensive than those with less

[23] The corresponding figure in the Canadian economy was 24% in 1996 (Baldwin and Gu, 2003).

[24] This is a high-tech classification of manufacturing industries based on the technological intensity and NACE Rev.2. as published by Eurostat.

Table 2.4: Summary Statistics (ii) - Annual Average of Exporter Share (2006-2015)

Within Industries	**Highest**	Electrical Equipment (79.8%) Chemical Products (79.1%) Motor Vehicles (75.1%)
	Lowest	Paper Products (52.1%) Wearing Apparel (47.0%) Non-Metallic Mineral Products (42.3%)
Across Industry	**Highest**	Electronics Products (14.2%) Transport Equipment (13.2%) Motor Vehicles (12.4%)
	Lowest	Furniture (2.28%) Repair and Installation (1.14%) Other Manufacturing (1.01%)

technological intensity.

Table 2.4 also presents the share of exporters that is accounted for by each and every industry across the whole manufacturing industry. It indicates that three medium-to-high technology industries - electronics products (14.2%), transport equipment (13.2%) and motor vehicles (12.4%) - account for just below 40%. As the matching method will be employed later, only a subset of the total exporters - export starters - will be employed to be compared with those with no experience of exporting. A detailed description of the method will be provided later.

2.3.3 Exporter Premia

Exporter premia has been one of the well established empirical facts in the relevant literature (e.g. Bernard et al., 1995), having been confirmed for a number of datasets. The same results can be found in Korean manufacturing as shown in Table 2.5. The table presents the comparison of simple means between the firms that export and those that do not. According to the table, the exporting firms are more productive, larger in terms of employee, capital and intermediate inputs. However, this needs to be cautiously interpreted as it does not take into account the panel structure. A more pertinent method to investigate the exporter premia is to run the following regression equation

$$FIRM_{it} = \beta_1 EXP_{it} + \beta_2 LogL_{it} + \delta_j + \delta_t + \epsilon_{it} \tag{2.20}$$

where $FIRM_{it}$ represents the firm-level characteristics (in logs) such as sales, capital, inter-

Table 2.5: Summary Statistics (iii) - Simple Comparison

		Mean	St. Dev.	25th	Median	75th	Obs
$LogY_{it}$	$EXP_{it}=1$	10.82	1.32	9.94	10.67	11.58	33,029
	$EXP_{it}=0$	10.02	1.06	9.49	10.09	10.80	17,583
L_{it}	$EXP_{it}=1$	379	2380	83	129	238	33,029
	$EXP_{it}=0$	136	289	67	91	140	17,583
$LogK_{it}$	$EXP_{it}=1$	9.602	1.48	8.67	9.49	10.38	33,015
	$EXP_{it}=0$	8.91	1.35	8.19	8.93	9.69	17,571
$LogM_{it}$	$EXP_{it}=1$	10.17	1.50	9.17	10.04	11.03	33,029
	$EXP_{it}=0$	9.34	1.50	8.56	9.39	10.23	17,583
$LogTFP_{it}$	$EXP_{it}=1$	5.51	0.44	5.21	5.44	5.72	28,471
	$EXP_{it}=0$	5.25	0.33	5.04	5.22	5.43	13,584

Note: EXP_{it} denotes a dummy variable that takes on 1 if the firm i exports at time t and zero otherwise.

mediate inputs and productivity. EXP_{it} represents a dummy variable which takes on 1 if a firm i exports at time t. $LogL_{it}$ is included to control for the size of firms. Industry (δ_j) and time (δ_t) fixed effects are also included.

Table 2.6 confirms the findings of exporter premia in the existing literature (e.g. Bernard et al., 1995; De Loecker, 2007). The results clearly show that the exporting firms differ from non-exporting firms in terms of sales, capital, intermediate inputs and productivity. It is worth noting that the exporeter premia holds true even when the control variables - size variables, indusry and time dummies - are included. The coefficient on EXP_{it} is statistically significant even under 1% level.

It is clear from the results that the exporting firms are significantly different from non-exporting firms, especially, in terms of productivity. However, the difference in productivity can result from two possible reasons; learning by exports and self-selection. Even though this chapter is interested in the former, the results from the above regression do not distinguish one from the other. Before discussing the empirical strategy to identify the learning by exports effects, it is worth investigating the evidence of self-selection.

Table 2.6: Fixed-effects Regression of Firm Characteristics on EXP_{it} Dummy Variable

	(1)	(2)	(3)	Obs
$LogY_{it}$	0.089***	0.062***	0.030***	50,612
	(0.007)	(0.006)	(0.006)	
$LogK_{it}$	0.075***	0.050***	0.025***	50,586
	(0.009)	(0.008)	(0.006)	
$LogM_{it}$	0.100***	0.0734***	0.051***	50,612
	(0.009)	(0.008)	(0.008)	
$LogTFP_{it}$	0.073***	0.068***	0.062***	42,055
	(0.002)	(0.002)	(0.002)	
Control				
Size	No	Yes	Yes	
Industry	No	No	Yes	
Time	No	No	Yes	

Note: Standard errors are reported in parentheses. ***,** and * indicate significance at 1%, 5% and 10% respectively.EXP_{it} represents a dummy variable which takes on 1 if a firm i exports at time t. Time fixed effects are included.

2.3.4 Self-Selection

The presence of fixed costs involved in the participation into the export market means that not all firms can become exporters (Melitz, 2003). There is still a possibility that only productive firms can afford to export and it is those productive firms that self-select into the export activity. Therefore, the natural question to ask is whether productive firms really self-select into exporting, by using the following regression

$$P(START_{it} = 1) = g(\mathbf{X}^{'}\beta + \delta_j + \delta_t + \epsilon_{it}) \tag{2.21}$$

where $START_{it}$ denotes a dummy variable which takes on unity if the firm is an export starter (as defined above) and zero for non-exporters[25]. $g(\cdot)$ denotes the logit function. $\mathbf{X}$ denotes a vector of firm-specific characteristics at $t-1$ which affects the firm's decision to offshore. These include TFP, the number of employees and capital, all of which are expressed in logs. The dummy variable FOR_{it}, which denotes the firm's status of foreign ownership, is also included. δ_j and δ_t denote the industry and time dummy variables respectively.

[25]Export starters are defined to be the firms with no experience of exporting at least during the previous two years. The same rule applies to those that quit and re-enter after at least two years of exporting activities. The information gathered during the status as an exporter, is likely to depreciate and the re-entry costs incurred by the past exporter are likely to be similar to those by the new entrants (Roberts and Tybout, 1997).

Table 2.7: Logit Regression

	Pooled	RE	FE
$LogTFP_{it-1}$	0.322^{***}	0.462^{***}	0.842^{***}
	(0.083)	(0.122)	(0.223)
$LogL_{it-1}$	0.123^{***}	0.195^{***}	0.349^{***}
	(0.039)	(0.058)	(0.105)
$LogK_{it-1}$	0.077^{***}	0.110^{***}	0.201^{***}
	(0.020)	(0.030)	(0.055)
FOR_{it-1}	0.554^{***}	0.703^{***}	1.261^{***}
	(0.044)	(0.065)	(0.116)
Observations	8,099	8,099	8,099
Chi2	559.55	320.55	318.63
Prob > chi2	0.0000	0.0000	0.0000

Notes : Standard errors are reported in parentheses. Industry and time dummies are included, but not reported in this table. * 10%, ** 5%, *** 1% level of significance.

Table 2.7 shows the results of the logit regression. The first column shows the results from the pooled logit model, correcting for clustering. The coefficients on productivity, employees and capital are all positive and significant under the 1% level. Also, the coefficient on FOR suggests that firms under foreign ownership are more likely to start exporting, possibly due to the ease with which they can engage in transactions with foreign buyers. The second and third columns show the results from random and fixed effects logit models respectively, in which unobserved firm-level heterogeneity is taken into account. The results, signs and levels of significance remain unchanged to those in the first column, only to confirm the self-selection hypothesis.

These results imply that the self-selection is at play in Korean manufacturing industry by which more productive and larger firms are becoming exporters. The likelihood becomes higher if the firm is under the foreign ownership. These findings imply that it is important to control for self-selection to avoid a potential bias in the estimation of the learning-by-export effects.

2.4 Empirical Strategies

As the presence of a self-selection mechanism was confirmed in the previous section, the interest now lies in the estimation of post-entry effects. In this chapter, the DID-PSM method is employed to control for self-selection bias as it has been found that it is a productive firm that self-selects into exporting (see Appendix B.2). By combining a PSM technique with DID estimation, a selection not only on observables but also on time-invariant unobservable firm-level characteristics can be controlled for.

The notation $\hat{\omega}_{it+s}$ is employed to denote RTFP at time $t+s$, which was measured using the method suggested in the previous section following the decision to start exporting at time $s=0$. Consequently, the average effect of exporting on productivity is defined as below

$$E[\hat{\omega}^1_{it+s} - \hat{\omega}^0_{it+s} | START_{it} = 1] = E[\hat{\omega}^1_{it+s} | START_{it} = 1] - E[\hat{\omega}^0_{it+s} | START_{it} = 1] \tag{2.22}$$

where $\hat{\omega}^1_{it+s}$ measures RTFP of the export starter i at time $t+s$, whereas $\hat{\omega}^0_{it+s}$ denotes RTFP of the same firm at time $t+s$ if it had remained non-exporter at time t. Also, $START_{it}$ takes on the value 1 if a firm i begins to export at $s=0$ and zero otherwise.

To construct a valid proxy for the unobservable $E[\hat{\omega}^0_{it+s} | START_{it} = 1]$, the PSM technique provides a criterion - a propensity score - by which the matched treated and control groups are created[26]. Based on the estimated propensity scores, a firm i that starts exporting at time t is paired up with a non-exporter j whose propensity score is closest to the former (i.e. nearest neighbour matching). Then, the estimation of the post-entry effects, denoted $\hat{\beta}_{EXP}$, can be expressed as below

$$\hat{\beta}_{EXP} = \frac{1}{N_{t+s}} \sum_i (\hat{\omega}^1_{it+s} - \sum_{j \in C_M(i)} w_{ij} \hat{\omega}^0_{jt+s}) \tag{2.23}$$

where N_{t+s} denotes the number of firms at time $t+s$ that decided to start exporting at time t. Let M denote the number of non-exporters matched with export starters i. In addition, $C_M(i)$ denotes the set of first M non-exporters j matched to the export starters i. Lastly, $w_{ij} = \frac{1}{M}$ if $j \in C_M(i)$ and $w_{ij} = 0$ otherwise. To improve the quality of matching, a number of

[26]Balance between the treatment and control groups is checked to confirm whether the matched treatment and control groups are observationally identical independently of treatment. Its procedure has been detailed in the appendix, so its description will be omitted in this chapter (see Appendix B.3).

restrictions have been placed. Firstly, matching is considered only in the space of common support. Secondly, an export starter and non-exporter are matched within the same year. This ensures that economy-wide macroeconomic shocks are controlled for. Thirdly, a caliper level - the maximum propensity score distance - has been set to as narrow as 0.01 to improve the performance of propensity score matching.

However, selection into exporting is not only dependent on observable but also on unobservable characteristics. Thus, the PSM approach is combined with a DID technique to control for unobservable firm-level characteristics as follows

$$\hat{\beta}_{DID-EXP} = \frac{1}{N_{t+s}} \sum_i (\Delta\hat{\omega}^1_{it+s} - \sum_{j \in C_M(i)} w_{ij} \Delta\hat{\omega}^0_{jt+s}) \tag{2.24}$$

where $\Delta\omega^1_{it+s}$ represents firm i's change in productivity before (in t-1) and after (in t+s, s = 0,1,2,3) beginning to export. Similarly, $\Delta\omega^0_{it+s}$ denotes firm i's change in the respective productivity, had the firm not started exporting. By differencing sequentially, firm-level time-invariant unobservable characteristics that affect a firm's decision to export can be controlled for. The DID-PSM method is known to improve the quality of non-experimental evaluation results significantly (Blundell and Dias, 2000).

2.5 Results

2.5.1 Learning-by-Exporting Effects

The main results are presented in this section regarding the effects of the decision to start exporting on the productivity level at time $s \in [0,3]$[27].

The results in Table 2.8 show that export has a positive and statistically significant effect on productivity. Once firms start exporting, they become, on average, 6.8% more productive (at s=0). The productivity gap remains more or less the same in later years, in the range of 5 to 6 %. At s=3, the productivity gap amounts to 6.1% and remains statistically significant

[27]As s increases, the number of firms decreases. It is either because the export starters stop exporting or exit the market or because that the non-exporters exit the market. Also, given that different firms enter the export market at different stages of time, the whole history cannot be traced for some of the export starters that enter late in the sample period.

Table 2.8: Learning-by-Exporting : Real Productivity with PSM

s	0	1	2	3
$\hat{\omega}_{it+s}$				
Treatment	5.430	5.433	5.449	5.451
Control	5.361	5.382	5.394	5.390
$\hat{\beta}_{EXP}$	0.068***	0.051***	0.050***	0.061***
S.E.	(0.01)	(0.01)	(0.01)	(0.02)
T-stat	4.39	3.22	2.73	2.92
# of treated	1,042	1,035	808	614
# of control	9,559	7,374	5,753	4,394

Notes : Standard errors are reported in parentheses. * 10%, ** 5%, *** 1% level of significance. s denotes the time between the decision to offshore and when the profit channel effect is estimated.

even under the 1% level. However, it should be reminded that selection on unobservable, but time-invariant, firm-level characteristics has not been controlled for in the PSM method.

This overall picture does not vary, even when applying the DID-PSM method. The results still show that exporting has a positive and statistically significant effect on productivity *growth*. When firms start exporting, their productivity grows faster than those that only serve the domestic market. According to Table 2.9, the productivity growth, with reference to the pre-entry productivity for export starters, was 6.9% higher than the non-exporters. The higher growth rates have eventually flattened, however even after 4 years of exporting, productivity growth of export starters is 3.1% higher than that of non-exporters. The difference is also statistically significant under the 1% level. This confirms the presence of learning-by-exporting effect.

2.5.2 Real TFP

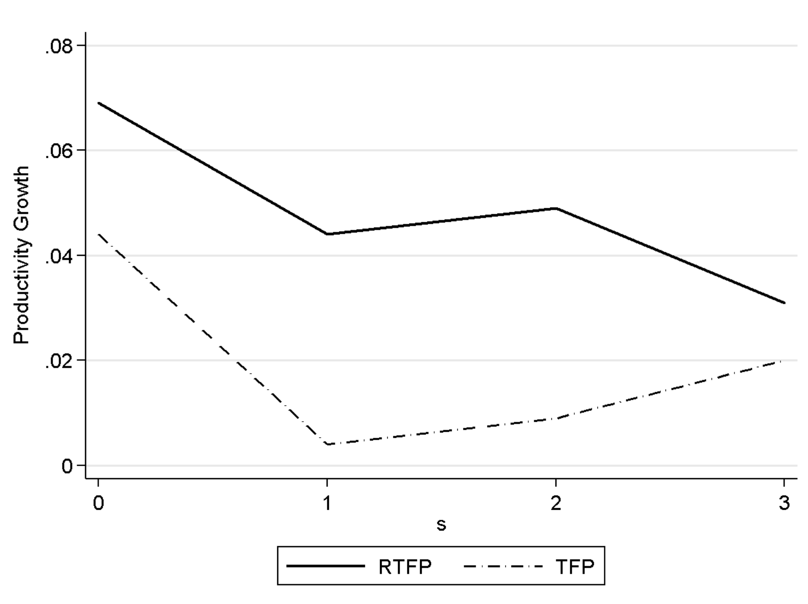
The results in Table 2.8 and 2.9 indicate that exporting has a positive effect on productivity. This confirms the presence of learning-by-exporting effects. It should be reminded that this chapter focuses on the development of real TFP from the instant that a firm decides to start exporting. This implies that the positive results found in the previous section are better related to an improvement in firm-level efficiency relative to the conventional TFP. If the latter measure, which is likely to be contaminated with transitory shocks or measurement errors, was employed as in the existing literature, the matching procedures would have

Table 2.9: Learning-by-Exporting : Real Productivity with DID-PSM

s	0	1	2	3
$\Delta\hat{\omega}_{it+s}$				
Treatment group	0.079	0.082	0.103	0.111
Control group	0.009	0.038	0.054	0.080
$\hat{\beta}_{DID-EXP}$	0.069^{***}	0.044^{***}	0.049^{***}	0.031^{***}
S.E.	(0.004)	(0.005)	(0.01)	(0.01)
T-stat	15.94	7.90	6.44	3.11
# of treated	1,042	1,035	808	614
# of control	9,559	7,374	5,753	4,394

Notes : Standard errors are reported in parentheses. * 10%, ** 5%, *** 1% level of significance. s denotes the time between the decision to offshore and when the profit channel effect is estimated.

Figure 2.3: Productivity Growth : RTFP vs TFP



produced less clear results on the link between export and productivity.

In Figure 2.3, the learning-by-exporting effects, $\hat{\beta}_{DID-EXP}$, are plotted using two different measures of productivity: RTFP (solid) and TFP (dotted). It shows that there is a marked difference in the trajectory of productivity growth. According to the figure, at $s = 0$, export starters are placed on different TFP growth trajectories (compared to the pre-entry productivity) depending on the measures. When RTFP is employed, at $s = 0$, export causes productivity growth to be approximately 7% higher compared to the pre-entry productivity. The high productivity growth tapers off in the later years, however, remaining positive and close to 4%.

However, if TFP is employed, at $s = 0$, export causes productivity growth to be higher, but at a lower rate than in the case of RTFP. Moreover, from $s = 1$, the learning-by-exporting effects quickly become trivial and productivity growth decreases to almost zero. Subsequently, it shows a gradually increasing trend, but the learning-by-exporting effect, when measured by TFP, is clearly short-lived.

The findings in Table 2.10 confirm that the learning-by-exporting effect becomes not only short-lived but also statistically insignificant even under the 10% level. Row (a) in Table 2.10 shows the learning-by-exporting effects when RTFP is employed. As already examined above, all the coefficients are positive and even highly significant. However, row (b) shows a contrasting picture. Productivity growth for export starters increases to 4.4% at s=0, but sharply decreases to 0.4%, which is negligible and even statistically insignificant.

This chapter does not argue that the learning-by-doing effect is better captured with RTFP than TFP, but argues that they clearly measure different aspects. In section 2.2.1, it was argued that RTFP is better related to firm's efficiency than TFP. It, of course, may be a coincidence that the learning-by-exporting effect is found to be positive and long-lasting when using RTFP in this chapter. The results would have differed - positive, short-lived, marginal and not significant - if TFP was employed. RTFP furnishes credibility to the positive learning-by-exporting effect as it can be said to be the result of improved efficiency rather than other factors that are not entirely related to the firm's decision to export.

2.5.3 Industry-level Learning-by-Exporting Effects

In section 2.5.1, the learning-by-exporting effect was investigated using the whole manufacturing sector. However, in this section, the same hypothesis is examined within the industries according to Korean Standard Industrial Classification (KSIC) at the level of 2-digit sections (see Appendix B.4). By performing matching within industries, industry-specific characteristics can be controlled for, to better analyse the effects of export on productivity. The findings in Table 2.11 show that the evidence of learning-by-doing effect is found in almost every industry with the exclusion of Rubber and Plastic Products (22), Furniture (31), Other Manufacturing (32) and Repair and Installation (33).

Table 2.10: Learning-by-Exporting : RTFP v. TFP

s	0	1	2	3
$\Delta\hat{\omega}_{it+s}$				
(a) $\hat{\beta}_{DID-EXP}$	0.069^{***}	0.044^{***}	0.049^{***}	0.031^{***}
$\Delta\omega_{it+s}$				
(b) $\hat{\beta}_{DID-EXP}$	0.044^{**}	0.004	0.009	0.020
# of treated	1,042	1,035	808	614
# of control	9,559	7,374	5,753	4,394

Notes : * 10%, ** 5%, *** 1% level of significance. s denotes the time between the decision to export and when the profit channel effect is estimated.

Table 2.11: Learning-by-Exporting : Industry-Level Learning-by-Exporting Effects ($\hat{\beta}_{DID-EXP}$)

s	0	1	2	3
Code				
13	0.035^{***}	0.013	0.059	−0.020
14	0.093^{***}	0.066^{***}	0.089^{**}	0.066
17	0.049^{***}	0.040	0.046	−0.011
20	0.067^{***}	0.060^{**}	0.079^{**}	0.076
22	0.024	0.018	0.027	−0.009
23	0.053^{**}	0.026	0.060^{*}	0.027
24	0.101^{***}	0.103^{***}	0.132^{***}	0.092^{***}
25	0.059^{***}	0.044^{***}	0.074^{**}	0.023
26	0.090^{***}	0.026	0.057^{**}	0.025
27	0.059^{***}	0.053	0.053	−0.052
28	0.069^{***}	0.046^{**}	0.024	0.066
29	0.053^{***}	0.036^{**}	0.020	−0.003
30	0.091^{***}	0.072^{***}	0.024	0.038
31	0.043	0.030	0.021	−0.056
32	0.055	−0.020	−0.022	0.001
33	−0.038	−0.177	−0.113	−0.083

Notes : * 10%, ** 5%, *** 1% level of significance. s denotes the time between the decision to export and when the profit channel effect is estimated.

Table 2.12: Learning-by-Exporting : Industry-Level Learning-by-Exporting Effects ($\hat{\beta}_{DID-EXP}$)

s	0	1	2	3
Low Technology				
$\hat{\beta}_{DID-EXP}$	0.048**	0.052***	0.083***	0.048**
S.E.	(0.02)	(0.01)	(0.02)	(0.02)
# of treated	149	148	124	98
# of control	2,016	1,572	1,237	947
Medium-Low Technology				
$\hat{\beta}_{DID-EXP}$	0.060***	0.049***	0.056***	0.058***
S.E.	(0.01)	(0.01)	(0.01)	(0.01)
# of treated	279	278	221	169
# of control	3,092	2,434	1,916	1,491
Medium-High Technology				
$\hat{\beta}_{DID-EXP}$	0.062***	0.045***	0.027**	0.028*
S.E.	(0.01)	(0.01)	(0.01)	(0.01)
# of treated	614	609	463	347
# of control	4,451	3,368	2,600	1,956

Notes : * 10%, ** 5%, *** 1% level of significance. s denotes the time between the decision to export and when the profit channel effect is estimated.

It is worth noting that there are large differences in the magnitude or durability of the effects across the industries. For example, in Basic Metals (24), export decision allows the productivity growth to be 10% higher than non-exporters after a year of exporting. The difference increases to 13.2% after three years of exporting (s=2). On the contrary, in Textiles (13), productivity growth for export starters is 3.5% higher compared to non-exporters in the very first year of exporting. However, the learning-by-exporting effect in the textile industry is found to be short-lived as the difference between the two groups becomes statistically insignificant in later years. The results need to be interpreted with caution because industry-level matching allows only a small number of export starters in each year. This small number observation provides insufficient power to produce meaningful results.

As aforementioned, the entire manufacturing sector is classified into three different categories: low technology, medium-low technology and medium-high technology industries.

According to these classifications, several industries can be grouped together according to their R&D intensities, defined to be the ratio of R&D expenditures to value-added. Examples of medium-high technology industries include computers or motor vehicles, whereas low-technology industries include textiles and wearing apparel (see Appendix A.4). Each industry differs from one another according to their dependence on technology and it is likely that there are category-specific factors that are commonly shared by industries in each category. This grouping allows to control for such category-specific factors as well as to overcome the issue of small samples noted in Table 2.11.

According to Table 2.12, the findings show that positive, and statistically significant, learning-by-exporting effects are found in all three industries. However, the trajectories they are placed on differ from one industry to another. In low-technology industry, export starters are placed on an increasing TFP growth trajectory as the difference in productivity growth compared to non-exporters starts from 4.8% and even increases to 8.3% after three years of exporting ($s = 2$). On the contrary, export starters in the medium-low technology sector start from 6.0%, and somewhat remaining at the similar rate even in later years. In the medium-high technology sector, export starters start with the highest rate of 6.2%, but the difference can be seen to plateau in later years down to 2.8% in s=3.

2.6 Effects of Exporting on Markups

The fact that sales variable, not quantity, is used as a proxy for output in the estimation of production function has implications; a positive effect from exporting which was observed in the previous section can be possibly attributed to the following two effects: improvement in technical efficiency or an increase in demand. Due to the data constraints, it is extremely difficult to isolate one effect from the other. However, with the estimates of markups at hand, the size of the latter effect can be indirectly estimable.

De Loecker and Warzynski (2012) provided a method to measure the markups with the usual variables available in the firm panel dataset that are based only on the imposition of cost-minimising behaviour to a firm. This greatly relaxes the data requirement often associated with the measurement of markup. Suppose a general production function $Q_{it} = Q_{it}(L_{it}, M_{it}, K_{it}, \omega_{it})$ whose only restrictions are to be continuous and twice differentiable with respect to its arguments. Q_{it}, L_{it}, M_{it} and K_{it} denote output, labour, intermediate inputs and capital stock of a firm i at time t. The first-order condition for a variable input M_{it} is given by

Table 2.13: Simple Regression of Firm-level Markups on Offshoring Decision

	(1)	(2)
γ_1	0.001	−0.006
	(0.005)	(0.005)
γ_2	-0.026^{***}	0.001
	(0.002)	(0.003)
γ_3	-0.052^{***}	0.001
	(0.006)	(0.006)
Controls		
X	Yes	Yes
Industry-Time	No	Yes
Obs.	38,936	38,936

Note: Standard errors are reported in parentheses. ***,** and * indicate significance at 1%, 5% and 10% respectively. The standard errors for μ_{OFF} are obtained from a non-linear combination of the estimated parameters.

$$\frac{\partial Q_{it}(\cdot)}{\partial M_{it}}\frac{M_{it}}{Q_{it}} = \frac{1}{\lambda_{it}}\frac{P^M_{it}M_{it}}{Q_{it}} \tag{2.25}$$

where P^M_{it} denotes a firm i's price for a variable input M at time t. λ_{it} denotes the Lagrangian multiplier, which is the marginal cost of production at a given level of output. Equation (2.25) shows that cost-minimising behaviour of a firm leads to the equality of the output elasticity of any variable input M_{it} to $\frac{1}{\lambda_{it}}\frac{P^M_{it}M_{it}}{Q_{it}}$. Consequently, by defining the markup as $\mu_{it} \equiv \frac{P_{it}}{\lambda_{it}}$., equation (2.25) can be re-written as

$$\theta^M_{it} = \mu_{it}\frac{P^M_{it}M_{it}}{P_{it}Q_{it}} \tag{2.26}$$

where θ^M_{it} denotes the output elasticity of an input M. The data on total sales ($P_{it}Q_{it}$) and the expenditure on intermediate inputs ($P^M_{it}M_{it}$) can be easily obtained from the dataset, whereas the output elasticity θ^M_{it} was already obtained from the previous section.

Exporting firms can be classified into three different categories: starters, exiters and continuers. Starters are defined to be firms which did not engage in exporting at least for two previous periods and have since started exporting. Exiters are the firms who engaged in exporting for at least two consecutive years and stopped exporting. Continuers are ones which engaged in exporting throughout the sample period. The regression equation is as follows

$$\ln\mu_{it} = \gamma_0 + \gamma_1 START_{it} + \gamma_2 EXIT_{it} + \gamma_3 CONTINUE_{it} + \mathbf{X'}_{it}\sigma + \delta_j + \delta_t + \epsilon_{it} \tag{2.27}$$

where $\ln\mu_{it}$ denotes the logged markups obtained from De Loecker and Warzynski (2012). $START_{it}$ is a dummy variable which denotes one if a firm i is a starter at time t and zero otherwise. In a similar vein, $EXIT_{it}$ ($CONTINUE_{it}$) is also a dummy variable which denotes 1 if a firm i is an exiter (continuer) at time t and zero otherwise. γ_1 captures the percentage difference in markups before and after the exporting decision. γ_2 also captures the percentage difference, but when a firm i stops exporting in t. $\mathbf{X}_{it}$ includes usual control variables for markups such as firm size, market structure (Herfindahl index) and offshoring status. Industry (δ_j) and time (δ_t) fixed effects are also included.

The coefficient of main interest lies in γ_1. Table 2.13 reports that the decision to start exporting has no positive impact on markups. The first row reports the coefficient of 0.001 in column (1) and -0.006 in (2). They are not only statistically insignificant even under the 10%, but also small in magnitude. This indicates that the decision to export is not significantly associated with any increase in markups.

If it is simply assumed that $\Delta\ln P_{it} \simeq \Delta\ln\mu_{it}$ (i.e. constant marginal costs), then the positive learning-by-exporting effects can be attributed to an increase in productivity. Clerides et al. (1998) find that firms' costs are not affected by previous exporting activities. However, a recent finding suggests that export entrants experience efficiency gains, that is, falling marginal costs (Garcia-Marin and Voigtländer, 2019). Part of gain in costs will be passed on to price levels, which may be able to explain non-significant change in markups. If this is the case, the productivity-enhancing effects, using sales data, are likely to be underestimated.

As the dataset at hand does not include detailed firm-level information, it is difficult to entirely isolate the productivity effect of exporting. However, under the assumption that marginal costs remain the same or decrease, this investigation into markups provides an indirect way of confirming the positive effect of exporting on productivity.

2.7 Conclusion

This chapter attempted to analyse the effect of exports on productivity in the context of the Korean manufacturing sector. Korea has long been a country whose reliance on trade is particularly high due to the small domestic market. Thus, the investigation into the link between export and firm-level productivity has greater significance than in any other countries.

The main focus lies in testing the learning-by-exporting hypothesis, that is, the post-entry effect on productivity. However, as the evidence for self-selection was noted in this chapter, the possibility of self-selection bias was raised. To control for the self-selection bias, the DID-PSM method was employed to control for firm-level characteristics that would affect a firm's decision to export. The findings show that export starters become 6.9% higher in productivity growth than those that only serve the domestic market. This confirms the presence of the learning-by-exporting effect in the Korean manufacturing sector.

The propensity score matching was also performed within each industry to control for industry-specific characteristics. The results show that the learning-by-exporting effects are found in almost every industry with the exclusion of only a few. Similar results were also found when the entire manufacturing sector was classified into three different industries according to the R&D intensities. These results confirm the support for the learning-by-exporting hypothesis in the Korean manufacturing sector.

This chapter also accounts for the fact that productivity is measured using sales variable rather than quantity variable. The resulting productivity measure was found to increase not only due to technical efficiency, but also to demand change. The current dataset is not detailed enough to isolate one effect from the other, but an alternative and indirect method is suggested in this chapter by investigating the link between markups and exporting to measure the magnitude of the latter effect. The empirical findings show no evidence of the link between markups and exporting, thus confirming the positive effect of exporting on productivity.

More importantly, a new measure of productivity is suggested in this chapter, more consistent with the notion used in the existing literature on export and productivity. Being a simple derivative from the conventional TFP, it was termed real TFP. The new measure is a portion of the conventional total factor productivity from which transitory shocks or measurement errors are removed. The latter two elements are part of the conventional TFP, but are not directly related to a firm's efficiency or managerial ability as they are often considered - or hoped - to be.

The positive, significant and long-lasting learning-by-exporting effects become short-lived and insignificant when the matching procedures are performed again with the conventional TFPs. This does not necessarily suggest that post-entry effects are better captured with the real total factor productivity. However, it is worth noting that, if a different - not even entirely relevant - productivity measure was used, this chapter would have produced results that do not support the learning-by-hypothesis.

Chapter 3

Does Offshoring Increase Productivity?

3.1 Introduction

Empirical research, based on micro datasets, has documented that firms that engage in international activities, such as exporting, importing and foreign direct investments, tend to be larger and more productive than firms that only serve the domestic market (Bernard et al., 1995, 2007). Offshoring is no exception. Tomiura (2007) has demonstrated that offshoring Japanese firms are distinctively more productive than domestic firms. An interesting aspect is that such differences between offshoring and non-offshoring firms exist even before offshoring activities commence.

This suggests that offshoring is positively correlated with firm's productivity because firms with high productivity self-select into offshoring activities. This self-selection hypothesis has not only been theoretically supported (Antràs and Helpman, 2004) but also been empirically confirmed by various authors. However, this is not the only channel relevant for the positive correlation (De Loecker, 2007). The second mechanism is the *post-(offshoring) entry*[1] hypothesis: firms which enter into offshoring markets not only have access to improved

[1]In the existing literature on exporting or importing, the term 'learning' has often been used to describe productivity enhancement which arises after firms enter into the international activities. By 'learning', the emphasis is placed on the fact that firms gain access to new knowledge and expertise. However, the term 'learning-by-offshoring' will not capture the entirety of possible mechanisms, many of which do not seem to be directly related to the term learning. De Loecker (2013) admits that 'learning' in learning by exporting actually refers to a variety of mechanisms that might bring about productivity increases after exporting such as marketing investments, product or process innovations or dealing with foreign buyers. Thus, this chapter opts for the term 'post-(offshoring) entry' rather than 'learning-by-offshoring'.

technology and technical expertise, but also an opportunity to reallocate resources in which they have comparative advantage (Grossman and Rossi-Hansberg, 2008)[2]. There is evidence of various research which examine the second channel and, barring minor differences, are broadly similar in that they find positive effects of offshoring on productivity. Examples include Görg and Hanley (2005), Hijzen et al. (2010), Jabbour (2010), Wagner (2011), Schwörer (2013) (See Appendix C.1).

This chapter mainly argues that offshoring has positive effects on productivity. It is found that firms which decide to start offshoring experience, on average, experience a positive change in productivity. This change in productivity is not only statistically significant, but also persistent. Moreover, it is found that the modifications, which will be suggested later on in addition to the Levinsohn-Petrin method, have brought about significant changes to the estimation of coefficients.

This paper contributes to the existing literature in a number of aspects. Firstly, the modified Levinsohn-Petrin (LP) method, which explicitly controls for selection bias in the spirit of Olley and Pakes (1996), is employed. This is especially relevant in the context of Korean manufacturing where exit and entry rates are not negligible and firms with lower productivity exit and become replaced by those with higher productivity (De Loecker, 2007). The explicit control for selection bias in the context of Levinsohn and Petrin (2003) was first attempted by Kasahara and Rodrigue (2008). However, it is argued in this chapter that their approach potentially leads to inconsistent estimation of capital in the second stage and value-added should be employed in place of gross sales to avoid this issue.

Secondly, offshorer status is included in the estimation procedures as an additional state variable[3]. This inclusion controls for differences in market structures and factor prices facing the firms when they make decisions regarding intermediate inputs and exiting the market. As Table 3.1 shows, McCann (2011), to my best knowledge, is the only paper which includes offshorer status in the estimation procedures amongst the related literature. If offshorer status is correlated with the inputs, which is likely, then its omission could lead to inconsistent input coefficients in the first stage.

[2] It needs to be noted that most of the research, including this one, uses productivity measures which reflect sales per inputs at the firm level. Therefore, an increase in the productivity measure may not only capture technological improvements, but also an increase in sales due to sourcing of cheaper intermediate inputs from abroad.

[3] Offshorers might choose a different level of intermediate inputs (and also have a different exit rule), controlling for capital and productivity, due to different market prospects (Van Biesebroeck, 2005). Offshorer status captures differences in domestic and foreign markets, which are assumed to have different input or output prices due to institutional barriers such as imperfect factor mobility or product differentiation depending on the intended markets of sale.

Table 3.1: Differences in the Productivity Measures in the Existing Literature

	Productivity Measure			
	Dependent Variable	OP or LP	Offshorer Status	Endogenous Markov Process
Görzig and Stephan (2002)	Sales per employee	×	×	×
Wagner (2011)	Sales per employee	×	×	×
Girma and Gorg (2004)	TFP	×	×	×
Schwörer (2013)	TFP	OLS	×	×
Görg et al. (2008)	TFP	LP	×	×
Hijzen et al. (2010)	TFP	OP	×	×
Jabbour (2010)	TFP	OP	×	×
McCann (2011)	TFP	OP	✓	×

Thirdly, this paper assumes an endogenous Markov process. The original LP method critically depends on the assumption of an exogenous first-order Markov process. However, because the main intention of this paper is to examine the role of offshoring in determining the evolution of firm-level productivity over time, endogenising productivity process is a necessary step[4]. If an exogenous Markov process is incorrectly assumed, productivity shock, which is used for the moment conditions, can contain variations arising from offshorer status. This can cause bias if a firm's capital stocks or intermediate inputs are correlated with it in the second stage. Table 3.1 shows that there has been no case of assuming an endogenous Markov process in the existing offshoring literature, even when the OP or LP was employed. This is concerning as there has been abundant theoretical and empirical evidence that offshorer status is likely to impact the capital.

Fourthly, this chapter also accounts for the fact that productivity is measured using sales variable rather than quantity variable. The resulting productivity measure can increase not

[4]This is equivalent to saying that productivity follows a first-order Markov process with transition probabilities $P(\omega_{it+1}|\omega_{it}, OS_{it})$, where OS_{it} denote the offshorer status at time t (Doraszelski and Jaumandreu, 2013).

only due to technical efficiency but also demand change. The current dataset is not sufficiently detailed to isolate one effect from the other, but an alternative and indirect method is suggested in this chapter by investigating the link between markups and offshoring to measure the magnitude of the latter effect.

Last but not least, this is, to the best knowledge, the first paper to investigate into the effects of offshoring on a Korean manufacturing firms' productivity using firm-level data. The existing literature looks at various countries and their manufacturing firms. However, it can be said that the existing literature lacks in diversity, as it is mostly confined to manufacturing firms in developed countries, which are expected to have had relatively long experiences of the business practice. The research on Asian manufacturing firms, except for Japan, is especially scarce because offshoring is a business practice that is not widely accepted amongst these countries. This is partly attributable to the fact that most have assumed the role of the offshoring destinations. However, given that the costs of coordinating far-flung operations may be inversely related to the level of experience, the relatively lower experience in offshoring may make its effects work out differently at firms in Asian countries. In this regard, the research on Korean manufacturing firms is expected to attenuate bias in the choice of countries and shed new light on the possibility of generalisation of almost unanimously positive effects of offshoring in the existing literature.

This chapter is organised as follows. Section 3.2 provides a literature review, with section 3.3 and 3.4 defining offshoring and presenting the data used for this chapter. Section 3.5 illustrates possible theoretical channels through which offshoring can affect firm-level productivity. Section 3.6 describes empirical strategies that this chapter has taken for the estimation of consistent production function coefficients and the derivation of firm-level productivity. Also, this chapter provides an empirical specification for the estimation of the effects of offshoring on firm-level productivity, with the interpretation of the results being given in section 3.7. Section 3.8 discusses the link between offshoring and markups as part of robustness check, with the last section concluding the chapter.

3.2 Literature Review

No economic issue has received as much media attention as offshoring[5]. As anxiety over potential job loss has been instigated by the media, the public have constantly taken to the streets and protested against a firms' decision to relocate their jobs abroad[6]. The size of job loss was unjustifiably feared to be massive (Amiti and Wei, 2004) and the issue has grown more and more politically charged (Olsen, 2006). Politicians have tried to appear sympathetic to the voters, who were fearing the possible loss of jobs due to offshoring.

Much academic research has followed to dismiss such fears among the public as disproportionately exaggerated. Amiti and Wei (2004) demonstrated that there were no significant effects on the U.S. manufacturing employment from its service offshoring. Drezner (2004), Baily and Farrell (2004), Mankiw and Swagel (2006) placed a projection of staggering 3.3 million job displacements *by 2015* into perspective recalling that "roughly 2 million Americans change jobs" *every month* (Baily and Farrell, 2004, p.5)[7]. Harrison and McMillan (2006) found that offshoring of the U.S. multinational manufacturing firms explains only a quarter of more than 4 million jobs lost over the period between 1977 and 1999[8].

Researchers went as far as to argue that there is a productivity-enhancing channel from offshoring. Initially, the research was based on industry-level data[9]. Amiti and Wei (2009)

[5] During the 2004 U.S. presidential election, offshoring was mentioned over 1000 times in four major newspapers (Mankiw and Swagel, 2006). Amiti and Wei (2004) also document that, in the space of five months between January and May 2004, there were over 2,500 reports in the U.S. newspapers about service offshoring.

[6] There have been numerous protests against offshoring decisions. In May 2004, members of Lloyds TSB group union protested and urged shareholders to oppose the firm's plan to outsource their U.K.-based jobs to India. On 30th July, 2012, airline pilots from United Airlines gathered in front of the White House to protest against the potential offshoring of their jobs. On 10th March, 2016, Chicago Nabisco workers protested against Mondelez International's plan to move its production work to Mexico.

[7] This is a convincing comparison, which can allay unjustifiably exaggerated fears of offshoring. However, utmost caution needs to be taken in this approach of interpreting the figure. 3.3 million over around ten years may look negligible compared to the monthly labour turnover in the U.S., but it does not necessarily mean that the suffering of those who may lose jobs is also negligible. The suffering may aggravate further as relations of power will be tilted in favour of firms which get to have access to new pools of talented workers, reducing bargaining power of all workers (Levy, 2005). If the labour market is not as flexible as it needs to be, policies need to be accompanied to smooth the transition period regardless of the size of those affected.

[8] Private sector think-tank McKinsey Global Institute (MGI) estimate that, by 2030, as many as *375 million* workers globally could switch to new occupational categories and learn new skills as a result of automation (Mankiya, J and Lund, S and Chui, M and Bughin, J and Woetzel, J and Batra, P and Ko, R and Sanghvi, 2018). This daunting estimate demonstrates that automation could be a real threat to job displacements than oft-blamed offshoring.

[9] Early empirical research using a firm-level data started from the early 2000s. Görzig and Stephan (2002) and Girma and Gorg (2004) investigated an effect of outsourcing on productivity of German and U.K. manufacturing firms respectively using a firm-level panel data. However, both of the research do not distinguish between domestic outsourcing and offshoring.

used the U.S. industry level input-output tables constructed by the Bureau of Labor Statistics. They particularly focus on the effects of service offshoring[10] whose intensity is defined as the purchases of services relative to the total intermediate input purchases[11]. **?**[12] also measured offshoring intensity of 12 European countries from EU input-output tables (EUROSTAT) to measure its effect on productivity of low-skilled labour in the European countries. However, the analysis with industry-level data is not sufficient, as acknowledged by the authors, in understanding the varying effects arising from firm heterogeneity.

As micro-level data on firm offshoring became available, there has been a continuing expansion in the investigation into the effects of offshoring on firm-level productivity. Using the Japanese manufacturing firm-level data, Hijzen et al. (2010) found that offshoring from foreign affiliates is positively correlated with productivity whereas that from a third party is not. Jabbour (2010) used the French firm-level data based on *Service Des Etudes Statistiques Industrielles*, that is exceptionally rich and includes information on the country of origin. Jabbour found that offshoring to developed countries had no significant effect, whereas that to developing countries exhibited significant and positive effects. Other examples include Görg and Hanley (2005), Görg et al. (2008), Wagner (2011) and Schwörer (2013).

The aforementioned papers are unanimously in support of the productivity-enhancing effect. This chapter examines if the productivity-enhancing effect is also experienced by Korean manufacturing firms, but relatively more emphasis is placed on the way productivity is measured. It is worth noting that the relevant literature is different in the way productivity is defined[13]. For example, labour productivity can be used a dependent variable, but Syver-

[10] Amiti and Wei (2009) chose five service industries - telecommunications, insurance, finance, business services and computing and information.

[11] Their measure for offshoring intensity follows Feenstra and Hanson (1996) in that it applies the economy-wide import ratio of inputs to all industries. As admitted by the authors, this is not an ideal practice. However, in a case where there is no access to the exact industry-level import data, it may serve as a "reasonable proxy of the proportion of imported inputs by industry" (Amiti and Wei, 2009, p210).

[12] The research stands out in that it uses Constant Elasticity of Substitution (CES) framework. Moreover, following Pirotte (1999), short-run parameter estimates are obtained by the fixed effects models, whereas the long-run counterparts are obtained by the cross-sectional estimator.

[13] There are a few differences in the empirical specification amongst the literature depending on

- whether total wage bills (Görg et al., 2008; Jabbour, 2010), intermediate inputs (Feenstra and Hanson, 1996) or gross outputs (Schwörer, 2013) are used as the denominator of the measures of offshoring intensity
- whether the location of source countries is considered (Jabbour, 2010) or not
- whether the type of offshored tasks is distinguished (Amiti and Wei, 2009) or not
- whether regression (Schwörer, 2013) or propensity score matching (Wagner, 2011) is employed

son (2011) points out that it is likely to be a misleading measure of firms' efficiency. Görg et al. (2008), Jabbour (2010) and Schwörer (2013) used what could be described as a better measure such as total factor productivity. However, they simply rely on the established semi-parametric methods such as Olley and Pakes (1996) or Levinsohn and Petrin (2003), without necessary modifications in line with the context of offshoring. This chapter aims to address the lack of due attention, as the inconsistent estimation of productivity may deliver a misleading indication that offshoring has an impact on productivity despite this not being the case, or vice versa.

3.3 Definition of Offshoring

Offshoring is fundamentally a relocation of tasks abroad. Although interchangeably used, offshoring and outsourcing need to be distinguished as one does not necessarily imply the other (Olsen, 2006). Whilst offshoring focuses more on the fact that the tasks are relocated *abroad* than the relocation itself, the opposite is true for outsourcing.

Table 3.2: Insourcing, Vertical FDI and Outsourcing

	Within Firms	**Between Firms**
Domestic	Domestic Insourcing	Domestic Outsourcing
Foreign	Vertical FDI	Offshore Outsourcing

Outsourcing refers to the relocation of tasks to external providers. This can be divided into two different types depending on whether they are relocated to domestic or foreign providers. The former is termed *domestic outsourcing* and the latter as *offshore outsourcing*. Offshoring, on the other hand, places more focus on the fact that the tasks are relocated to foreign providers. This can be further divided into two different types depending whether the providers are an affiliate or an unaffiliated firm. The former is termed *captive offshoring (vertical FDI)*[14] and the latter is named *offshore outsourcing*[15]. Thus, offshoring and out-

[14]FDIs can be classified into two types depending on their original purposes. Horizontal FDI refers to the undertaking of the same production activities in foreign markets. The main aim of the horizontal FDI is an entry into other foreign markets. On the other hand, vertical FDI refers to the relocation of the part of production activities abroad. One of the main reasons for vertical FDI is to make use of cheap resources abroad.

[15]There has been some 'muddles' over offshoring even amongst scholars. Bhagwati et al. (2004) argued that

sourcing coincide only when a firm opts to contract out its in-house activities to arm's length foreign vendors. Otherwise, the interchangeable use needs to be paid particular attention. This is illustrated in Table 3.2. Firm-level offshoring intensity is often measured using survey data. More detail on its construction will be referred to in Appendix C.2.

3.4 Data

3.4.1 Survey of Business Activities

This chapter uses the Survey of Business Activities (SBA) provided by the Statistics Korea (KOSTAT). This is the annual survey data that covers all enterprises with at least 50 employees or 300 million won capital and covers the period from 2006 to 2015. An enterprise can be defined as the minimum institutional unit as a producer of goods and services and an independent accounting unit in charge of its own profits and losses[16]. The data provides information not only on sales, wages, material costs, investments or tangible assets, but also on enterprise-level activities such as research and development, outsourcing activities and business strategies. This survey was first conducted in 2006, as the need for enterprise-level data mounted and has continued since then. Although the survey covers every industry in Korea, this research is particularly concerned with the manufacturing sector, which is identified with two-digit Korea Standard Industrial Classification (KSIC) codes (see Appendix B.4)[17].

As the values are recorded in nominal values, they are deflated into real values to be used in the estimation. This chapter follows the existing literature in using an industry-level price data to deflate nominal values (e.g. Hijzen et al., 2010; Ahn and Choi, 2016)[18]. Real sales

only offshore outsourcing should be the subject of discussion over offshoring. However, Trefler et al. (2005) argued that both have to be considered as offshoring by pointing out that there are the practical difficulties of refining the definition of offshoring. In this chapter, the principle is that offshoring is defined to be the relocation of activities to foreign countries, regardless of its form, with the proviso that *those were and could have been made in-house*.

[16]This differs from *establishment* which is 'an enterprise, or part of an enterprise, that is situated in a single location and in which only a single productive activity is carried out or in which the principal productive activity accounts for most of the value added" (United Nations, 2008, p.87). Establishment is also the smallest unit capable of providing information on the questionnaire (Girma and Gorg, 2004).

[17]Two industries are excluded out of 24: Tobacco Products and Printing and Reproduction of Recorded Media. The former industry was excluded as there are only few observations reported in each period and the latter as it was not possible to obtain an appropriate price deflator.

[18]Industry-level deflator is commonly used in the literature due to the absence of information on prices for each firm. However, De Loecker (2007) pointed out that the use of industry-level price deflator can result in

are defined as the nominal sales obtained directly from SBA divided by the industry-level Producer Price Index (PPI), which is provided by Economic Statistics System (ECOS) from the Bank of Korea (BoK). Nominal capital and investment are deflated by Domestic Supply Price Indexes[19] for capital equipment from the same source. Lastly, the real intermediate inputs are defined as nominal intermediate inputs deflated by Domestic Supply Price Indexes (DSPI) for intermediate materials which are also compiled by the BoK. They also provide two different types of DSPI for domestic and foreign intermediate inputs, which are then used to deflate imported materials from domestic and foreign vendors respectively.

3.4.2 Descriptive Evidence

Firm-level variables such as sales, employment, capital and intermediate inputs are reported in Table 3.3. It is observed that offshorers[20] are likely to be larger in size, in terms of both outputs and inputs, and more productive than outsourcers and non-outsourcers. This shows the existence of offshorer premia, which will be discussed in more detail in the section 3.4.3. It is also worth noting that there is outsourcer premia, to a lesser degree, especially in terms of capital and productivity.

Table 3.4 shows the average share of offshorer, outsourcer and non-outsourcer between 2006 and 2015. The average share of offshorer stands at 6.3%. This pales in comparison to the share of outsourcer which amounts to 75.4%. The share of firms that neither offshore nor outsource is as high as 18.1%. This indicates that the practice of offshoring is a business practice that is not widely adopted across the industries and implies that the Korean manufacturing firms rely heavily on domestic outsourcing, rather than offshoring. This observation is consistent with the theoretical prediction that offshoring is a costly process, for which firms with low productivity cannot afford (Antràs and Helpman, 2004).

Figure 3.1.(a) displays the share of offshorers over the period of 2006 to 2015 and shows that there is no consistent trend in the share of offshorers. Having peaked at 7% in 2006, it has

a so-called price bias. For example, if an individual firm is able to negotiate a lower price for the purchase of inputs, then the use of a (higher) industry-level deflator can lead to an under-estimation of inputs and the resulting over-estimation of TFPs without any real change (Van Beveren, 2012). This issue will be discussed more in the later section.

[19]Producer Price Index (PPI) measures the average changes over time in prices received by domestic producers for their goods and services. Domestic Supply Price Indexes (DSPI) are derived from the PPI and Import Price Index (IPI). They are calculated by splitting the individual item's weight from PPI and IPI in accordance with its proportion in each stage of production and add these items up by raw materials, intermediate materials and services and final goods and services.

[20]More detailed description on the terms is given in the note below

Table 3.3: Summary Statistics

		Mean	St. Dev.	25th	Median	75th	Obs
Sales	Offshorer	11.28	1.41	10.33	11.15	11.96	3,196
	Outsourcer	10.60	1.24	9.74	10.42	11.25	38,211
	Non-outsourcer	10.55	1.30	9.67	10.40	11.32	9,205
Employment	Offshorer	684	3976	93	160	314	3,196
	Outsourcer	268	1487	75	111	198	38,211
	Non-outsourcer	271	2414	71	102	178	9,205
Capital	Offshorer	9.48	1.74	8.45	9.39	10.35	3,194
	Outsourcer	9.37	1.43	8.50	9.30	10.15	38,195
	Non-outsourcer	9.25	1.55	8.36	9.23	10.14	9,197
Intermediate Inputs	Offshorer	10.46	1.61	9.50	10.34	11.30	3,196
	Outsourcer	9.85	1.51	8.92	9.74	10.68	38,211
	Non-outsourcer	9.83	1.65	8.91	9.82	10.83	9,205
TFP	Offshorer	5.55	1.30	4.57	5.51	6.55	2,580
	Outsourcer	5.32	1.12	4.55	5.35	6.02	30,697
	Non-outsourcer	5.15	1.25	4.26	5.06	5.94	7,096

Note: Sales, capital and intermediate inputs are expressed in real values and logs. Employment refers to the number of workers. A firm i is classified as offshorer if it offshores at time t. Similarly, outsourcer is a firm if it conducts domestic outsourcing, not offshoring, at time t. Finally, non-outsourcer is a firm which neither offshores nor outsources at time t.

Table 3.4: Average Offshorer/Outsourcer/Non-outsourcer Share

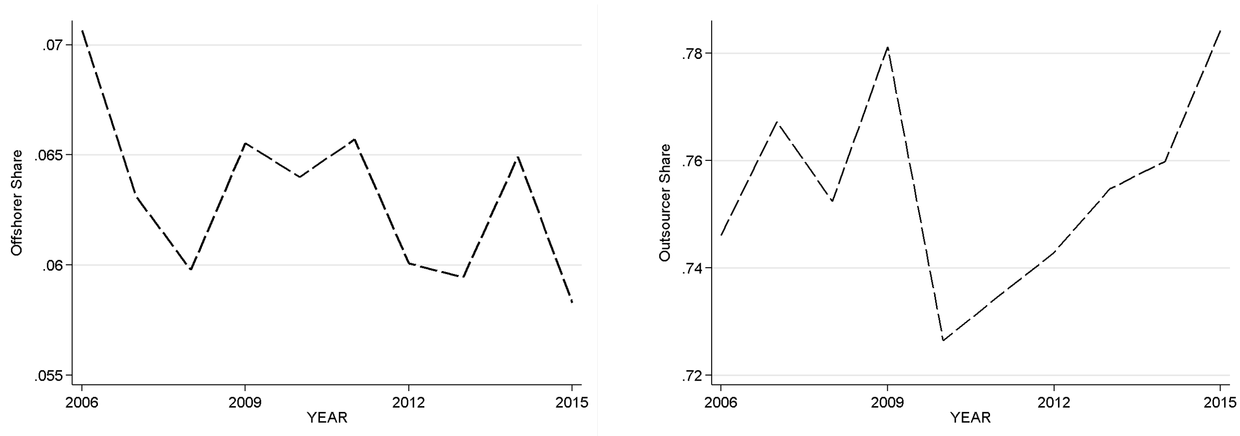
	Average (2006 - 2015)
(1) Number of Offshorers	320
(2) Number of Outsourcers	3821
(3) Number of Non-outsourcers	920
(4) Number of Firms	5010
(1)/(4)	6.3%
(2)/(4)	75.4%
(3)/(4)	18.1%

displayed slight fluctuations over the period. It is worth noting that the share ranges from approximately 6 to 7% and does not deviate too widely from the average share (6.3%). On the other hand, the share of outsourcers recorded 72.6% in 2011 and has shown a consistently increasing trend since then, reaching 78.4% in 2015. This suggests that there is an

Figure 3.1: Share of Offshorer/Outsourcer over Time

(a) Share of Offshorer over Time

(b) Share of Outsourcer over Time



Note : The share of offshorer/outsourcer at time t is defined as the number of offshorer/outsourcer at time t divided by the number of active firms at the same time.

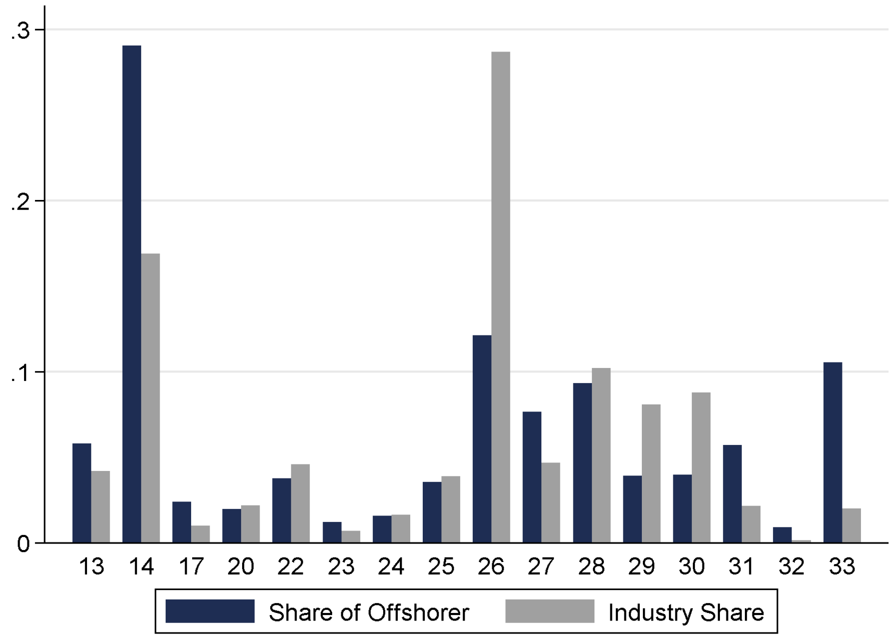
increasingly larger share of outsourcers in the Korean manufacturing industry, eclipsing the share of non-outsourcers.

In Figure 3.2, data for the share of offshorers in each industry is represented by the solid blue columns. On average, 30 % of the firms in Wearing Apparel (14) offshore each year, followed by Computer, Electronic and Optical products (26, henceforth, “Computer”) at more than 10 %. The Computer industry is closely followed by Electrical Equipment (27), Machinery and Equipment (28) and Repair and Installation of Machinery and Equipment (33, henceforth, “Repair and Installation”). On the other hand, the grey columns represent an industry share of total offshorers. It is observed that the sum of the shares of three largest industries amounts to more than half the total share. This demonstrates that these are the industries where offshoring is active, not just within, but also across the industries. It is also worth noting that the few industries, such as Repair and Installation, now record a very low share in the latter statistics.

Figure 3.3 plots the time-series of average offshoring intensity between the years 2006 and 2015. Offshoring intensity is defined as the ratio of real purchases of intermediate inputs from foreign providers to real sales of the firm [21]. In the run-up to the 2008 financial crisis, it shows a declining trend in the intensity. Since then, the intensity shows a mildly increasing trend, reaching at the pre-crisis level in 2015. This time trend suggests that, even though

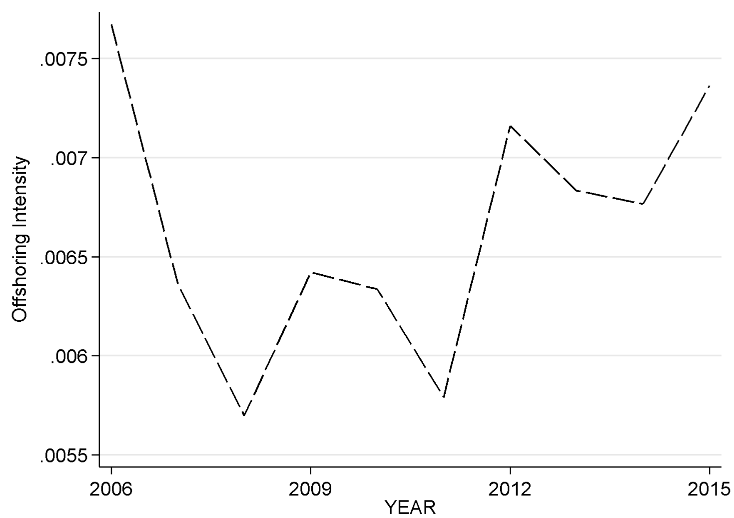
[21]The relevant issues regarding the measure for offshoring intensity are detailed in Appendix C.2.

Figure 3.2: Share of Offshorer and Industry Share of Offshorer



Note : The share of offshorer in each industry is an average of the share across time. The industry share of offshorer is also an average value of each industry's share of the total offshorers across time.

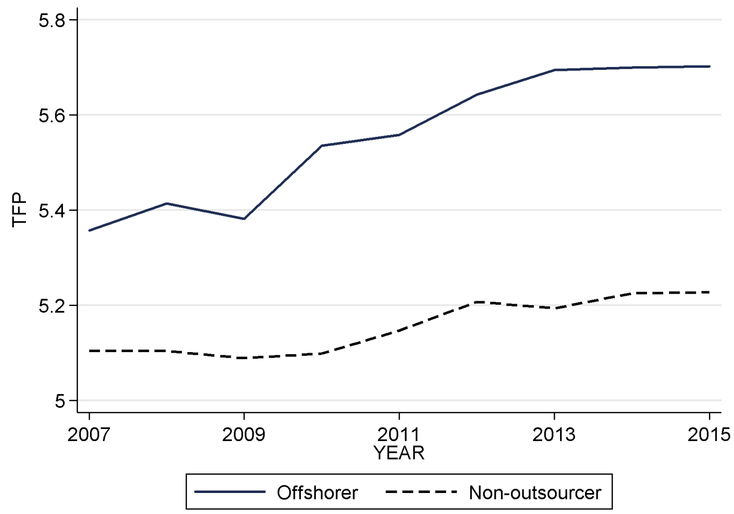
Figure 3.3: Time Series of Average Offshoring Intensity



offshoring is not widely pursued by a wide range of firms across the industries, the intensity has gradually deepened since 2008.

This chapter investigates the link between offshoring and productivity. As part of a visual

Figure 3.4: TFP Comparison Between Offshorers and Non-Outsourcers



inspection, Figure 3.4 plots two different time series of mean TFPs between offshorers and non-outsourcers. It is clear that the mean TFPs of offshorers have been gradually increasing. Interestingly, those of non-outsourcers display a similarly increasing trend during the same period, but at a distinctively lower rate.

Figure 3.5 compares the distributions of TFPs between offshorers and non-outsourcers. It is interesting to note that the distributions of non-outsourcers have remained more or less the same over the sample period. However, those of offshorers have steadily shifted rightwards, implying the overall increase in productivity. This coincides with the increasing trend of offshoring intensity shown in Figure 3.4. However, caution needs to be exercised as this does not provide sufficient information on causal direction.

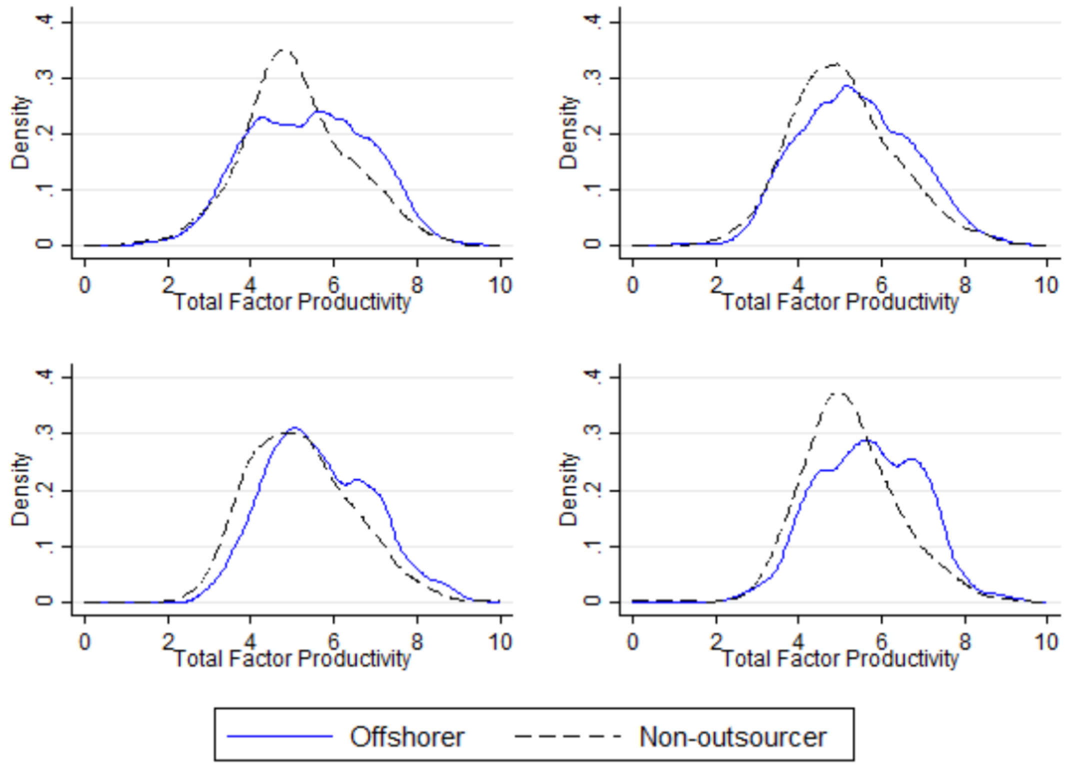
3.4.3 Offshorer Premia

The descriptive evidence in Table 3.3 suggests that offshorers are likely to be larger and more productive than those that do not offshore (*offshorer premia*). Following the related literature (e.g. exporter premia by Wagner, 2007), offshorer premia can be estimated using the regression equation

$$FIRM_{it} = \beta_1 OS_{it} + \beta_2 DS_{it} + \alpha_i + \gamma_t + \epsilon_{it} \tag{3.1}$$

where $FIRM_{it}$ represents the firm-level characteristics (in logs) such as sales, employment,

Figure 3.5: Comparison of Distribution of TFPs Between Offshorers and Non-outsourcers



Note : Top Left (2007), Top Right (2009) , Bottom Left (2012), Bottom Right (2015)

capital, intermediate inputs and productivity. OS_{it} represents a dummy variable which takes on 1 if a firm i is an offshorer at time t. Moreover, DS_{it} represents a dummy variable which takes on 1 if a firm i is an outsourcer at time t. Firm and time fixed effects are included.

Table 3.5 shows the results of a simple regression of firm-level characteristics on both OS_{it} and DS_{it} using a fixed-effects model for the entire sample of firms. The results suggest the existence of offshorer (as well as outsourcer) premia. The mean difference between offshorers and non-outsourcers is greatest in sales and the difference ranges from 6 to 8 % for the remaining variables. The mean productivity difference between offshorers and non-outsourcers is approximately 9.6%.

Aside from the mean productivity premium, quantile regression allows one to estimate offshorer productivity premium along the different points of the conditional distribution. In this paper, quantile regression with firm-level fixed effects has been employed à la Powell and Wagner (2011). Table 3.6 shows the different results over the different quantiles. The

Table 3.5: Simple Regression of Firm Characteristics on Offshorer and Outsourcer Dummy Variables

	OS_{it}	DS_{it}	Obs
Log Y_{it}	0.119^{***}	0.068^{***}	50,612
	(0.017)	(0.008)	
Log L_{it}	0.075^{***}	0.037^{***}	50,612
	(0.011)	(0.005)	
Log K_{it}	0.072^{***}	0.035^{***}	50 ,586
	(0.020)	(0.010)	
Log M_{it}	0.079^{***}	0.068^{***}	50,612
	(0.021)	(0.009)	
Log TFP_{it}	0.096^{***}	0.034^{***}	40,373
	(0.014)	(0.008)	

Note: Standard errors are reported in parentheses. ***,** and * indicate significance at 1%, 5% and 10% respectively. OS_{it} is a dummy variable which takes on 1 if firm i offshores at time t. DS_{it} is a dummy variable which takes on 1 if firm i conducts domestic outsourcing at time t. Time fixed effects are included.

second column shows the productivity premium of offshorers relative to non-outsourcers. The magnitudes range approximately from 7 to 16 % across the different quantiles and the offshorer productivity premium is statistically significant bar at the 90th quantile. This is broadly consistent with Antràs and Helpman (2004) in that offshorers are more productive throughout the entire distribution.

Offshorer premia can be interpreted that offshoring has a positive impact on productivity through post-entry effects. However, it can also be the case that offshorers are more productive than those who do not offshore to begin with and self-select into offshoring. Furthermroe, should a fixed cost exists, when firms start offshoring (e.g. search costs for a foreign supplier), only the firms with high productivity would be able to engage in offshoring. This presence of self-selection is examined in section 3.7.1.

3.5 Theoretical Backgrounds

Offshoring can theoretically be productivity-enhancing as firms' other international activities such as exporting, importing or foreign direct investment. However, it is distinctively different in that offshoring does not solely rely on technology diffusion or learning. It is also

Table 3.6: Fixed Effects Quantile Regression of Firm Productivity on Offshorer and Outsourcer Dummy Variables

Quantile	OS_{it}	DS_{it}
10th	0.101^{**}	0.050^{**}
20th	0.120^{***}	0.029
30th	0.075^{**}	0.030^{*}
40th	0.076^{**}	0.041^{***}
50th	0.089^{**}	0.038^{**}
60th	0.069^{**}	0.031^{*}
70th	0.122^{***}	0.032
80th	0.167^{***}	0.036^{*}
90th	0.024	−0.010

Note: ***,** and * indicate significance at 1%, 5% and 10% respectively. OS_{it} is a dummy variable which takes on 1 if firm i offshores at time t. DS_{it} is a dummy variable which takes on 1 if firm i conducts domestic outsourcing at time t. Firm and time fixed effects are included.

expected to enhance productivity by reallocating resources from less productive areas towards more productive ones. This argument becomes more apparent if it is understood that a manufacturing firm is usually composed of departments that contribute to its overall operation, such as production, quality, sales and marketing, corporate support or accounting. In other words, offshoring promotes productivity enhancement by increasing each department's productivity via technological diffusion, as well as by efficiently reallocating resources between them.

To examine the possible theoretical link from offshoring to firm-level productivity, this chapter defines firm i's productivity at time t as the aggregation of productivity across departments j, weighted by their output shares. This can be written as

$$\omega_{it} = \sum_{j} z_{ijt}\kappa_{ijt} \tag{3.2}$$

where κ_{ijt} denotes department j's productivity of firm i at time t. Moreover, z_{ijt} denotes the output shares of department j in firm i at time t and are used as weights in aggregating the department-level productivities κ_{ijt}. The simple manipulation of $\Delta\omega_{it} = \omega_{it} - \omega_{it-1}$ allows the firm-level productivity growth to be decomposed into the following two components.

$$\Delta\omega_{it} = \underbrace{\sum_j z_{ijt-1}(\kappa_{ijt} - \kappa_{ijt-1})}_{\text{Within-department Effects}} + \underbrace{\sum_j (z_{ijt} - z_{ijt-1})\kappa_{ijt}}_{\text{Reallocation Effects}} \tag{3.3}$$

In (3.3), the first term captures the contribution to the firm-level productivity from the productivity increase within the departments, whereas the second term captures the contribution from the output-share changes between the departments[22]. This demonstrates why offshoring is distinctively different from other international activities such as exporting and importing. Usually, the researchers focus on learning from the international activities and the resulting increase in productivity within the departments, hence the firm. However, offshoring also entails reallocation effects, whereby resources are allocated from less efficient to more efficient departments. This chapter examines how these two terms are related to oft-mentioned mechanisms from offshoring to productivity.

Firstly, there is a productivity gain from compositional effects. Offshoring refers to the relocation of a component of the departmental activities (or the entire activities) to a foreign provider. Because the foreign provider specialises in the offshored activities, it is expected to perform them at a lower cost or with higher efficiency. Offshoring, in this regard, can be considered as a replacement of the activities within the department with the offshored ones. The replacement will result in the productivity increase within the department as long as the foreign provider supplies the same activities, but with higher efficiency.

Even if the foreign provider is as efficient as the offshoring department, offshoring usually involves the replacement of in-house activities with those provided at a lower cost[23]. This allows the firm to save on production costs, freeing up resources which were locked in relatively less efficient departments. The freed-up resources can then be allocated back to departments in which they have comparative advantages. As a result, more productive departments will grow in size and the firm-level productivity will increase as a result (reallocation effects).

Secondly, one can anticipate that offshoring gives the same set of productivity-enhancing effects as that expected from a firm's importing activities. For example, offshoring allows firms to have access to a variety of inputs (Broda and Weinstein, 2006). This expanding

[22] Melitz and Polanec (2009) pointed out that this simple decomposition is not sufficient in various aspects, but this chapter will not offer the detail of their argument here. However, the simple decomposition is sufficient to deliver my point.

[23] Along with the access to skilled and qualified workers abroad, lower labour costs are reported to be one of the major reasons for offshoring. For this reason, in the theoretical frameworks, offshoring is defined to be the relocation of activities from North to firms in South where the labour costs are lower (e.g. **?**Naghavi and Ottaviano, 2009; Grossman and Rossi-Hansberg, 2008).

variety can be productivity-enhancing for reason of better match. As firms access a wide range of imported intermediate inputs from other countries, markets become "thicker." This implies that, as long as domestic and imported inputs are imperfect substitutes, firms are more likely to find inputs that better match their specific needs (McLaren, 2003). Moreover, offshoring firms can benefit from spillover effects whilst interacting with foreign suppliers. Therefore, offshoring will open a direct channel through which embodied and disembodied technologies can continuously flow (within-department effects) (Keller, 2004)[24].

Last but not least, offshoring can increase productivity as cost savings can be ploughed back into innovation activities such as R&D[25]. The process of Schumpeterian creative destruction, for example, provides a theoretical basis for understanding the motivation of a firm to reinvest cost savings into R&D (**?**). The successful innovator captures the monopoly rents from its innovation during the time interval until the next innovator replaces the current one, hence the term *creative destruction*. The empirical evidence on post-entry into R&D investment has been well documented. Görg and Hanley (2011) found a positive link between offshore outsourcing of services and innovation activity manifested in R&D at the plant level. An increase in R&D expenditures from offshoring activities can lead to an increase in firm-level productivity (Hall and Mairesse, 1995), which may be through within-department effects.

3.6 Empirical Strategies

3.6.1 Part I : Productivity Estimation

To measure the effects of offshoring on a firm's total factor productivity, it is foremost important to correctly identify the production function parameters. The first step is to specify the Cobb-Douglas production function as below

$$Y_{it} = K_{it}^{\beta_k} L_{it}^{\beta_l} e^{\omega_{it}+\eta_{it}} \tag{3.4}$$

[24]The former type of technology refers to new technology embodied in new equipment or new personnel. In contrast, the latter type of technology refers either to codified technology through licensing or offshoring or uncodified knowledge (De Beule and Nauwelaerts, 2013).

[25]This dynamic effect of offshoring interestingly appears in the arguments of David Ricardo, the author often credited with his theory of static comparative advantage. He maintained that increased profits from the exploitation of free trade can be used to increase productivity-enhancing investment. This again proves Keynes' comment that any idea is hardly exempt from any intellectual influences of some old economists.

where Y_{it} represents value-added - gross output net of intermediate inputs. The reason for choosing value-added over goes output will be explained later. K_{it} and L_{it} represent capital and labour of firm i at time t respectively, with β_k and β_l representing the corresponding parameters. ω_{it} subsumes the constant term and represents a productivity observable only to the firm. This may capture "managerial ability or expected down-time of machinery or changes in the manufacturing environment" (McCann, 2011, p.103). η_{it} is an i.i.d error term unknown to both firm and econometrician before a decision on inputs is made. Taking logs on (3.4),

$$y_{it} = \beta_k k_{it} + \beta_l l_{it} + \omega_{it} + \eta_{it} \tag{3.5}$$

where variables in logs are written in lower case. ω_{it} results not only from pure technological change, but also from the improvement in the efficiency and intensity in the use of inputs (Comin and Hobijn, 2010). This is measured by the proportion of output, which is not explicitly explained by the inputs of production as below

$$\text{TFP}_{it} = \hat{\omega}_{it} = y_{it} - \hat{\beta}_k k_{it} - \hat{\beta}_l l_{it} \tag{3.6}$$

for which unbiased estimation of their coefficients needs to be ensured. However, simply using OLS in the estimation of (3.5) is likely to produce biased coefficients as a result of simultaneity and selection issues.

Simultaneity bias is defined as the correlation between input choices and ω_{it}. If input choices are based on ω_{it}, a firm with a higher productivity shock is likely to hire more inputs. Consequently, the OLS estimates for more responsive variables to a productivity shock will tend to be overestimated than for other less responsive variables (Levinsohn and Petrin, 2003). The OP or LP method allows for the correction of simultaneity bias without having recourse to instruments. This is important as it is difficult to find good instruments in practice (De Loecker, 2007).

In addition, selection bias can also arise as a firm makes input choices conditional *on its survival* (Ackerberg et al., 2007). Intuitively, firms with a small capital stock are unlikely to survive the realisation of low productivity, whereas those with a large capital stock are likely to survive even the very low productivity shocks. Unless this selection issue is accounted for, one may be misled into concluding that low outputs are correlated with a high level of capital, leading to a downward bias in the coefficient on capital. Selection bias will become more

Table 3.7: Annual Exit and Entry Rates

	Annual
Offshorer Exit Rates	5.75%
Offshorer Entry Rates	3.27%
Outsourcer Exit Rates	6.04%
Outsourcer Entry Rates	5.32%
Non-outsourcer Exit Rates	7.86%
Non-outsourcer Entry Rates	8.76%

Note: The annual exit (entry) rate is defined as the number of firm exits (entries) in a given year divided by the total number of active firms in the previous year. The reported value is the mean of the annual exit (entry) rates.

relevant if the process of exits and entries is dynamic within industries. Table 3.7 reports the annual exit and entry rates for the Korean manufacturing firms during the sample period.

The extended LP method offers to correct for both simultaneity and selection biases. However, unlike the OP method, the original LP method (Levinsohn and Petrin, 2003) does not account for selection bias. Levinsohn and Petrin (2003) argued that the use of an unbalanced panel implicitly accounts for the exit and entry of firms, therefore controlling for the selection bias, to some extent. However, Van Beveren (2012) pointed out that failure to explicitly consider the exit decision of a firm can still lead to a selection bias.

In addition, it is explicitly assumed that offshoring (and outsourcing) firms face different market structures and factor prices when making decisions regarding intermediate inputs, by including the offshorer status variable in the intermediate inputs as in Van Biesebroeck (2005) and De Loecker (2007). The inclusion is driven by the observations that offshoring firms tend to be larger in terms of production inputs (see **3.4.3**). Therefore, the following equation will be employed

$$m_{it} = m_t(k_{it}, \omega_{it}, OS_{it}, DS_{it}) \tag{3.7}$$

where OS_{it} and DS_{it} represent offshorer and outsourcer status variables of firm i at time t respectively[26].

[26]Griliches and Mairesse (1995) noted that a strong assumption is placed on (3.7) by indexing m by t to allow for differences in these variables across time, that is, due to macro variables . However, it does not allow for individual differences across firms as they are not captured by the state variables. If firm-specific variables

The status variables are also included in the exit rule as additional state variables. This inclusion is related to the fact that offshorers and outsourcers tend to be more capital intensive. Therefore, the state variables k_{it}, OS_{it-1} and DS_{it-1} now become relevant for a firm's decision to exit[27]. It is observed in Table 3.7 that exit rates for non-offshoring firms are higher than those for offshoring firms on average. The explicit inclusion of a status variable helps to avoid biased estimation of the coefficients on intermediate and capital inputs in the second stage of the empirical strategy. For example, if it is not accounted for when it is correlated with intermediate inputs, then the coefficient will be upwardly biased.

First Stage

Olley and Pakes (1996) present a semiparametric method to circumvent these issues in which a firm's investment is used as a proxy variable to control for ω_{it}. Levinsohn and Petrin (2003) suggested using intermediate inputs as a proxy by focusing on the fact that firms make lumpy investments due to substantial adjustment costs. Ackerberg et al. (2015) noted that the essence of both methods is that one can invert optimal input decisions to have a non-parametric function of unobserved productivity shocks, under certain assumptions[28]. From (3.7),

$$\omega_{it} = m_t^{-1}(k_{it}, m_{it}, OS_{it}, DS_{it}) = j_t(k_{it}, m_{it}, OS_{it}, DS_{it}) \tag{3.8}$$

where $m_t^{-1}(\cdot) = j_t(\cdot)$ is a function of the observables k_{it} and m_{it}[29]. The invertibility of the function is conditional on the fact that intermediate inputs are strictly increasing in productivity [30]. In (3.5), ω_{it} is replaced by $j_t(\cdot)$,

such as exogenous intermediate input prices are observed, they can be included. However, Ackerberg et al. (2015) noted that "the premise of most of this literature is that such variables are either not available or not believed to be exogenous (p.2418)".

[27]The threshold productivity is related to the liquidation value, which in turn depends on the firm's capital stock.

[28]Refer to Pakes (1991) for the investment proxy and Levinsohn and Petrin (2003) for the intermediate input proxy.

[29]By allowing the functions to differ only across time t, but not across firms, it implicitly rules out any firm-level heterogeneity in demand or labour market conditions. Ackerberg et al. (2015) point out that the premise of the related literature is that one cannot observe exogenous, across-firm, variation in those variables such as input prices. If they were observable, then they can be included in the variable functions.

[30]In the original Olley-Pakes method, due to the monotonicity condition, observations with zero investment are truncated from the estimation. If there are non-negligible zero investment observations, the Olley-Pakes (OP) method could rather lead to a great efficiency loss (Van Beveren, 2012). In the data obtained from SBA, a significant number of firms report zero investment, undermining the efficiency of the results from the OP method. It is found that there are 1385 zero investment observations, which is considered to be non-negligible.

$$y_{it} = \beta_k k_{it} + \beta_l l_{it} + j_t(k_{it}, m_{it}, OS_{it}, DS_{it}) + \eta_{it} \tag{3.9}$$

Defining a new function $\phi_t(\cdot) = \beta_k k_{it} + j_t(\cdot)$,

$$y_{it} = \beta_l l_{it} + \phi_t(k_{it}, m_{it}, OS_{it}, DS_{it}) + \eta_{it} \tag{3.10}$$

This regression can be estimated by approximating $\phi_t(\cdot)$ using a certain high-order polynomial in k_{it}, m_{it}, OS_{it} and DS_{it}. From this, a consistent estimate of the coefficients for a variable input (labour) can be obtained. However, the coefficients on capital and intermediate inputs cannot be isolated as $\frac{\partial y_{it}}{\partial k_{it}} = \beta_k + j_t^{'}(\cdot)$ and $\frac{\partial y_{it}}{\partial m_{it}} = \beta_m + j_t^{'}(\cdot)$.

Second Stage

In the second stage, the coefficients on the state variables are estimated. Unlike the LP method, a firm's survival is accounted for in the spirit of Olley and Pakes (1996) (see Appendix C.3). To this end, a few assumptions need to be in place. Firstly, for every period, after observing the productivity shock ω_{it}, it is assumed that a firm makes an exit decision depending on the following exit rule

$$\chi_{it} = \begin{cases} 1 & \text{if } \ \omega_{it} \geq \underline{\omega}_t(k_{it}, OS_{it-1}, DS_{it-1}) \\ 0 & \text{if } \ \text{otherwise} \end{cases} \tag{3.11}$$

where χ_{it} is a survival indicator and $\underline{\omega}_t(k_{it}, OS_{it-1}, DS_{it-1})$ is a cut-off productivity *endogenously* determined in equilibrium. It can be observed that the three state variables k_{it}, OS_{it-1} and DS_{it-1} are now relevant for a firm's endogenous exit decision. Intuitively, firms with larger capital stocks are likely to self-select into offshoring (or domestic outsourcing) and are likely to continue in operation at even lower realisation of ω_{it} (Olley and Pakes, 1996). As shown in Table 3.7, the lower exit rates of offshorer and outsourcer relative to non-outsourcer also empirically prove this point.

Secondly, it is also assume that the productivity ω_{it} follows an endogenous Markov process as below

For some reasons, there were also observations with zero material inputs. This is something unexpected as Petrin et al. (2004) note that firms 'almost always report positive use of intermediate inputs' (p. 114). However, its number is much less than half that of zero investments. Thus, this chapter alternatively uses intermediate inputs as a proxy for ω_{it} following the Levinsohn and Petrin method.

$$\omega_{it+1} = E[\omega_{it+1}|\omega_{it}, OS_{it}, DS_{it}, \chi_{it+1} = 1] + \zeta_{it+1} \tag{3.12}$$

where ζ_{it+1} is a productivity innovation independent of ω_{it}, OS_{it} and DS_{it}. The inclusion of lagged offshoring-related variables is based on empirical research in which offshoring or domestic outsourcing is found to be positively correlated with productivity (e.g. Görg and Hanley, 2005; Görg et al., 2008; Hijzen et al., 2010; Jabbour, 2010; Wagner, 2011; Schwörer, 2013). De Loecker (2013) suggests that the past experience be included in the Markov process, which is often assumed to be exogenous. For example, if the offshoring status at $t-1$ is correlated with the capital stock at t through investment at $t-1$, this will lead to biased estimates of the coefficients. Consider the regression equation (3.5) in the next period,

$$\begin{aligned} y_{it+1} &= \beta_k k_{it+1} + \beta_l l_{it+1} + \omega_{it+1} + \eta_{it+1} \\ &= \beta_k k_{it+1} + \beta_l l_{it+1} + E[\omega_{it+1}|\omega_{it}, OS_{it}, DS_{it}, \chi_{it+1} = 1] + \zeta_{it+1} + \eta_{it+1} \\ &= \beta_k k_{it+1} + \beta_l l_{it+1} + g(P_{it}, \phi_{it} - \beta_k k_{it}, OS_{it}, DS_{it}) + \zeta_{it+1} + \eta_{it+1} \end{aligned} \tag{3.13}$$

where $g(P_{it}, \phi_{it} - \beta_k k_{it}, OS_{it}, DS_{it}) = E[\omega_{it+1}|\omega_{it}, OS_{it}, DS_{it}, \chi_{it+1} = 1]$[31]. In the first stage, the estimates of β_l and ϕ_{it} were obtained. Moreover, the probit regression of survival dummy

31

$$\begin{aligned} E[\omega_{it+1}|\omega_{it}, OS_{it}, DS_{it}, \chi_{it+1} = 1] &= \int_{\underline{\omega}_{it+1}} \omega_{it+1} f(\omega_{it+1}|\omega_{it}, OS_{it}, DS_{it}) d\omega_{it+1} \\ &= \int_{\underline{\omega}_{it+1}} \omega_{it+1} \frac{f(\omega_{it+1}, \omega_{it}, OS_{it}, DS_{it})}{\int_{\underline{\omega}_{it+1}} f(\omega_{it+1}, \omega_{it}, OS_{it}, DS_{it}) d\omega_{it+1}} d\omega_{it+1} \\ &= g(\underline{\omega}_{it+1}, \omega_{it}, OS_{it}, DS_{it}) \\ &= g(P_{it}, \phi_{it} - \beta_k k_{it}, OS_{it}, DS_{it}) \end{aligned}$$

where $\underline{\omega}_{it+1}$ denote the exit threshold at $t+1$. The fourth equality necessitates the definition of P_{it}, which is the probability of continuing into time $t+1$. It is defined as below

$$\begin{aligned} Pr(\chi_{it+1} = 1) &= Pr(\omega_{it+1} \geq \underline{\omega}_{it+1}(k_{it+1}, OS_{it}, DS_{it}) | \underline{\omega}_{it+1}(k_{it+1}, OS_{it}, DS_{it}), \omega_{it}, OS_{it}, DS_{it}) \\ &= \varphi_t(\underline{\omega}_{it+1}(k_{it+1}, OS_{it}, DS_{it}), \omega_{it}, OS_{it}, DS_{it}) \\ &= \varphi_t(k_{it+1}, k_{it}, m_{it}, OS_{it}, DS_{it}) \\ &\equiv P_{it} \end{aligned}$$

, where the third equality follows from (3.10) [i.e. $\omega_{it} = j_t(k_{it}, m_{it}, OS_{it}, DS_{it})$]. A probit regression of the survival dummy on $\varphi_t(k_{it+1}, k_{it}, m_{it}, OS_{it}, DS_{it})$ will result in its estimate $\hat{P}_{it}$.

$$\begin{aligned} g(\underline{\omega}_{it+1}, \omega_{it}, OS_{it}, DS_{it}) &= g[\varphi_t^{-1}(P_{it}, \phi_{it} - \beta_k k_{it}, OS_{it}, DS_{it}), \phi_{it} - \beta_k k_{it}, OS_{it}, DS_{it}] \\ &\equiv g(P_{it}, \phi_{it} - \beta_k k_{it}, OS_{it}, DS_{it}) \end{aligned}$$

on $k_{it+1}, k_{it}, m_{it}, OS_{it}$ and DS_{it} allows the estimation of P_{it}. By subtracting the known variation of labour,

$$y_{it+1} - \hat{\beta}_l l_{it+1} = \beta_k k_{it+1} + g(\hat{P}_{it}, \hat{\phi}_{it} - \beta_k k_{it}, OS_{it}, DS_{it}) + \zeta_{it+1} + \eta_{it+1} \tag{3.14}$$

Equation (3.14) demonstrates the need for the first stage and the use of value-added instead of gross output. Since capital is assumed to be dynamic, ζ_{it+1} is mean independent of all variable known at $t+1$. However, as both labour and intermediate inputs are chosen after the realisation of productivity, l_{it+1} and m_{it+1} are not mean independent of the disturbance in (3.14). This explains why value-added needs to be used as the dependent variable rather than gross output.

Because equation (3.14) is non-linear in β_k, non-linear least squares regression has been employed to obtain its consistent estimate. The non-parametric function $g(\cdot)$ is then approximated by higher-order polynomials in $\hat{P}_{it}$, $\hat{\phi}_{it}$, OS_{it}, DS_{it} to approximate non-parametric function $g(\cdot)$ by using a higher order series approximation.

The estimation results for labour and capital coefficients using the modified Levinsohn and Petrin method (henceforth, "LPMOD") are reported in Appendix C.4. It can be seen that the coefficients are mostly significant. The results from LPMOD are expected to correct for any bias arising from omitted offshoring and outsourcing status. This correction is not expected from the original LP method (henceforth, "LPEXT") where an exogenous Markov process is employed. Appendix C.5 demonstrates that the capital coefficients from LPEXT are generally higher than those from LPMOD. This upward bias in the capital coefficient was already suspected as the previous status implies a higher investment and, accordingly, a higher capital in the next period.

Using the coefficients from LPMOD, the resulting TFP estimates are reported in Appendix C.6. Its mean is reported along with its overall, between and within standard deviation. It is demonstrated that there is a wide variation in TFP estimates from industry to industry. Moreover, it is also worth noting that a between-firm standard deviation of TFP estimates is almost twice as large as a 'within-firm' standard deviation, suggestive of large heterogeneity in productivity across firms and a relatively sticky progress in productivity within firms.

3.6.2 Part II : Post-entry Effects Estimation using Difference-in-differences Approach

With the consistent estimates of TFPs in the previous section, a propensity score matching (henceforth, ”PSM”) difference-in-differences (henceforth, ”DID”) method is employed to evaluate the causal impact of offshoring. It has been observed in the previous section that offshorers tend to be more productive compared to non-outsourcers. Moreover, productive firms have been shown to be more likely to self-select into offshoring. To control for selection bias, Rosenbaum and Rubin (1983) suggested the PSM approach to alleviate potential selection bias on observed variables. This chapter also combines the PSM technique with DID estimation to control for selection on the unobserved, but time-invariant, firm-level characteristics.

Let ω_{it+s} be defined as the total factor productivity at time $t+s$ measured using the modified Levinsohn-Petrin method, following the decision to start offshoring at time $s=0$. The term ω^1_{it+s} measures the productivity of the firm i at time $t+s$, whereas ω^0_{it+s} denotes the productivity of the same firm at time $t+s$ if it had not begun offshoring at time t. The superscript denotes its status. The causal effect can be measured by the difference $\omega^1_{it+s}-\omega^0_{it+s}$. However, as the latter term ω^0_{it+s} is not observable, the average effect of offshoring on productivity can alternatively be defined as below

$$E[\omega^1_{it+s}-\omega^0_{it+s}|START_{it}=1]=E[\omega^1_{it+s}|START_{it}=1]-E[\omega^0_{it+s}|START_{it}=1] \tag{3.15}$$

where $START_{it}$ takes on the value 1 if a firm i starts to offshore at $s=0$ and zero otherwise. The dummy variable switches to one when a firm did not offshore for at least the previous two periods and starts to offshore in t. The issue lies in identifying the last term in (3.15), that is, the average productivity of firms that start offshoring, had they not done so. Instead, only $E[\omega^0_{it+s}|START_{it}=0]$ can be calculated, which inevitably leads to selection bias as follows

$$\text{Bias}=E[\omega^0_{it+s}|START_{it}=1]-E[\omega^0_{it+s}|START_{it}=0] \tag{3.16}$$

If the treatment was randomly assigned, it would suggest that offshoring starters[32] and

[32]Offshoring starters are defined to be firms which did not engage in offshoring at least for two previous periods and start offshoring.

purely domestic firms have the same observable and non-observable characteristics, hence no bias. However, as examined in the previous section, selection into treatment is not random, but is rather affected by many observable characteristics and, possibly, by non-observable characteristics. If this issue is not solved, the difference in productivity cannot be attributable solely to the firm's decision to offshore.

With matching techniques, a valid proxy for the unobserved $E[\omega^0_{it+s}|OS_{it}=1]$ can be constructed. The basic idea of matching is to construct a group of offshoring starters whose characteristics are similar to purely domestic firms in all pre-offshoring observable characteristics. The similarity between the two groups can be measured by propensity score - predicted probability to start offshoring - as suggested by Rosenbaum and Rubin (1983)[33]. The PSM technique rests on the assumption that selection into offshoring is completely conditional on a vector of the observable characteristics[34]. The inclusion of the pre-entry level of the outcome variable $\omega_{i,t-1}$ is especially important to control for self-selection bias. This assumption ensures that the matched firms are observationally identical on average and the treatment is randomly assigned.

The propensity score is estimated using a probit regression model. As possible determinants of entry to offshoring, This chapter includes productivity (ω), the number of employees (l) and capital (k). The variable for innovation intensity (RD), which is measured by the level of R&D as a fraction of gross sales is also included to control for the self-selection of highly innovative firms into offshoring. The dummy variables of exporter status (EXP) and foreign ownership (FOR) are further included as an additional determinant. Time and industry fixed effects are included as δ_t and δ_j respectively. Subsequently, the following probit regression can be estimated to obtain the propensity score of offshoring starters

$$P(START_{it}=1)=\Phi(\omega_{it-1}, l_{it-1}, k_{it-1}, RD_{it-1}, EXP_{it-1}, FOR_{it-1}) \tag{3.17}$$

The propensity score matching is essentially a weighing scheme where the estimated propensity scores are used to determine the weights placed on the comparison units in the control group (Rajeev and Wahba, 2005). There are various matching methods depending on weighing schemes. This chapter employs the kernel and radius matching methods. This is because

[33]It is unlikely to find matches for the treated if matches are attempted on many, especially continuous, variables. This is known as the curse of dimensionality. However, the propensity score can be used as a yardstick with which a similarity between the two observations is measured.

[34]In reality, a comprehensive list of the relevant variables is unlikely to come by. This chapter includes a range of variables which have been cited as the factors likely to affect a firm's decision to start offshoring in the literature.

the nearest neighbour matching would discard a large number of observations in the control group that are not matched, which would apparently lead to reduced power (Stuart, 2010). Consequently, the post-entry effect, denoted β_{OFF}, can be expressed as below

$$\beta_{OFF} = \frac{1}{N_{t+s}} \sum_{i} (\omega^{1}_{it+s} - \sum_{j \in C_M(i)} w_{ij} \omega^{0}_{jt+s}) \tag{3.18}$$

where N_{t+s} denotes the number of firms at time $t+s$ that have decided to offshore at time t. Also, $C_M(i)$ denotes the set of domestic firms matched to the offshoring starter i. To improve the quality of matching, further restrictions have been placed. Firstly, matching is restricted in the space of common support. This restriction ensures that only the observations in the overlap of the support of the propensity score are considered. Secondly, firms are matched from the same year, ensuring that the influence of macroeconomic shocks on matching is minimised.

Since matching is conditioned on the propensity score and not on observable characteristics, it needs to be investigated whether the distribution of observable (and unobservable) characteristics between the matched treated and control groups is the same independently of treatment. This can be done by testing the hypothesis that the means of each observable characteristic do not differ amongst them. Should the hypothesis be rejected, a different specification needs to be considered and tested again. This procedure ensures that offshoring and non-offshoring firms are observationally identical on average for a given propensity score.

The matching procedure so far, however, is not able to deal with the self-selection bias due to unobservable characteristics. Thus, the PSM approach is combined with a DID technique to control for unobservable firm-level characteristics. In the DID-PSM method, the difference in productivity before and after offshoring for the offshoring starter is compared to the corresponding difference for its counterpart. This is equivalent to estimating a fixed effects model, in which time-invariant unobservable characteristics are controlled for.

Let $\Delta\omega^{1}_{it+s}$ represent firm i's change in productivity before (in t-1) and after (in t+s, s = 0,1,2,3) entering the offshoring arrangements. Similarly, $\Delta\omega^{0}_{it+s}$ denotes firm i's change in the respective productivity, had the firm not entered the offshoring arrangements. Then, the estimation of the post-entry effect under the DID-PSM method, denoted $\beta_{DID-OFF}$, can be expressed as below

$$\beta_{DID-OFF} = \frac{1}{N_{t+s}} \sum_i (\Delta\omega^1_{it+s} - \sum_{j \in C_M(i)} w_{ij} \Delta\omega^0_{jt+s}) \tag{3.19}$$

where the notations remain consistent as in (3.18). By differencing sequentially, firm-level time-invariant unobservable characteristics, which also affect the firm's decision to offshore, can be controlled for. The DID-PSM method is known to significantly improve the quality of non-experimental evaluation results (Blundell and Dias, 2000).

3.7 Results

3.7.1 Self-Selection Bias?

To estimate the propensity score, the probit model (3.17) for the selection into offshoring is estimated based on certain observable characteristics in time $t-1$. Table 3.8 shows the results of this probit regression. Column (1) indicates that there is no evidence of self-selection into offshoring. However, when industry and time dummies are included, it becomes positive and highly significant under the 1% level, shown in column (2). This finding is consistent with the theoretical prediction (Melitz, 2003) and the vast literature related to the productivity and international activities (Bernard and Jensen, 1999; Wagner, 2007; Aw et al., 2007).

The variable for innovation intensity is also included to control for the possibility of highly innovative firms self-selecting into offshoring. In column (2), the coefficient on the innovation intensity (in terms of R&D investment) is positive and statistically significant. This is in line with the empirical findings that more innovative and productive firms have a higher propensity to self-select into offshoring[35].

The coefficient on employment is also positive and statistically significant at the 1 % level in column (2). This confirms the positive size effect on the probability of offshoring, suggesting that larger firms are more likely to self-select into offshoring. Similarly, the coefficient on the lagged dummy variable for foreign ownership is also positive and highly significant at 1 % level. Firms under foreign ownership may have relative strength compared to purely domestic firms in terms of the ease of engaging in international activities. This positive link between foreign ownership and a propensity to start offshoring is consistent with the

[35] The self-selection hypothesis is supported in the majority of the relevant literature, but there are a few exceptions. For example, Fryges and Wagner (2010) do not find any support for the self-selection hypothesis.

Table 3.8: Probit Regression : Selection into Offshoring

Variable	(1)	(2)
ω_{it-1}	-0.002	0.091^{***}
	(0.015)	(0.025)
l_{it-1}	0.176^{***}	0.090^{***}
	(0.025)	(0.027)
k_{it-1}	-0.071^{***}	-0.025
	(0.015)	(0.017)
RD_{it-1}	0.413^{**}	0.261^{*}
	(0.206)	(0.158)
FOR_{it-1}	0.477^{***}	0.422^{***}
	(0.040)	(0.040)
EXP_{it-1}	0.027	0.029
	(0.041)	(0.043)
Constant	-2.584^{***}	-3.374^{***}
	(0.108)	(0.178)
Time Dummies	No	Yes
Industry Dummies	No	Yes
Observations	33,012	32,677
Pseudo R^2	0.0485	0.0761
Prob > chi2	0.0000	0.0000

Notes : Standard errors are reported in parentheses. Industry and time dummies are included, but not reported in this table. * 10%, ** 5%, *** 1% level of significance.

empirical finding of Aitken et al. (1997). However, the coefficient on the lagged export status variable is positive but not statistically significant, even under the 10% level.

The results in this section are as follows: larger, more innovative and productive firms under foreign ownership tend to have a higher propensity to start offshoring. This suggests that, when measuring the post-entry effect, it is crucial to control for self-selection bias.

Table 3.9: Offshoring and TFP (i) - ω^{MOD}_{it+s}

s	0	1	2
(a) Kernel			
β_{OFF}	0.080	0.059	0.032
S.E.	(0.05)	(0.05)	(0.06)
T-stat	1.59	1.08	0.51
(b) Radius			
β_{OFF}	0.055	0.027	0.006
S.E.	(0.05)	(0.05)	(0.06)
T-stat	1.09	0.50	0.10

Notes : Standard errors are reported in parentheses. * 10%, ** 5%, *** 1% level of significance.

3.7.2 DID-PSM results

In this section, the results from the the application of the DID-PSM estimators are reported. In Figure 3.4, the average TFP trajectories for the unmatched offshorers and non-outsourcers can be observed. They show that offshorers are, on average, more productive than non-outsourcers. This potentially informs us that offshorers were already more productive, even before starting offshoring. However, the trajectories may also suggest the possible post-entry effect of offshoring on productivity.

Table 3.9 shows the estimates obtained using the cross-sectional propensity score matching. The productivity of a firm which starts offshoring at time t is compared with that of the matched non-outsourcers. This chapter follows the matched group of offshorering starters and purely domestic firms by denoting $s = 0, 1, 2$ as the time periods after the decision to start offshoring. Moreover, a further distinction is made by employing two different matching methods, the kernel and radius matching in rows (a) and (b) respectively. The results are similar, showing that the they are robust to the change in the matching methods. More importantly, this chapter deliberately denotes the productivity measured from the modified LP method as ω^{MOD}_{it+s} to distinguish it from ω^{LEV}_{it+s}, the productivity measure obtained from the original LP method.

Row (a) of Table 3.9 indicates that offshoring has a higher positive impact on the level of productivity in comparison to that of purely domestic firms. However, the result is statistically insignificant, albeit only marginally so in the first year. A similar result is obtained

Table 3.10: Offshoring and TFP (ii) - $\Delta\omega_{it+s}^{MOD}$

s	0	1	2
(a) Kernel			
$\beta_{DID-OFF}$	0.067^{***}	0.042	0.058
S.E.	(0.01)	(0.03)	(0.04)
T-stat	4.39	1.35	1.44
(b) Radius			
$\beta_{DID-OFF}$	0.066^{***}	0.038	0.046
S.E.	(0.01)	(0.03)	(0.04)
T-stat	4.35	1.23	1.14
#. Treated	583	360	288
#. Non-Treated	31,006	20,525	16,000

Notes : Standard errors are reported in parentheses. * 10%, ** 5%, *** 1% level of significance.

Table 3.11: Offshoring and TFP (iii) - $\Delta\omega_{it+s}^{MOD}$ vs $\Delta\omega_{it+s}^{LEV}$

s	0	1	2
(a) $\Delta\omega_{it+s}^{MOD}$			
$\beta_{DID-OFF}$	0.067^{***}	0.042	0.058
S.E.	(0.01)	(0.03)	(0.04)
T-stat	4.39	1.35	1.44
(b) $\Delta\omega_{it+s}^{LEV}$			
$\beta_{DID-OFF}$	0.108^{***}	0.052^{*}	0.056
S.E.	(0.02)	(0.03)	(0.03)
T-stat	4.64	1.73	1.61
#. Treated	583	360	288
#. Non-Treated	31,006	20,525	16,000

Notes : Standard errors are reported in parentheses. * 10%, ** 5%, *** 1% level of significance.

even when the radius matching method is employed, as shown in row (b). The magnitude of coefficients has marginally decreased, they remain statistically insignificant. The results seem to suggest that there is no evidence in support of the post-entry effect. However, it needs to be noted that, although the PSM method helps to mitigate selection bias, it does not control for selection-bias arising from unobserved firm-level characteristics. If not properly controlled for, the results from the PSM method can still suffer from self-selection bias.

Table 3.10 shows the results from the DID-PSM method. Row (a) indicates that offshoring has a positive and highly significant effect on the growth rate of productivity in the first year of offshoring ($s = 0$). The coefficient is reported to be 6.7% and significant even under the 1% level. This suggests that the average growth rate in productivity of offshorers is higher that that of non-outsourcers. However, this positive effect is only transient and can no longer be seen from $s = 1$, with the coefficients becoming insignificant in the second and third years of offshoring. The results are robust to the matching method as row (b) shows that there is a statistically significant productivity-enhancing effect in the first year of offshoring.

The results in rows (a) and (b) indicate that there is a positive instantaneous effect of offshoring on productivity. This can be regarded as evidence for the compositional effect, which results from a replacement of the activities within firms with the offshored ones. Moreover, as they can reallocate their resources towards the activities in which they have a comparative advantage, offshoring is expected to boost firm-level productivity in a relatively short space of time. However, the insignificant coefficients in later years do not seem to support the possibility of productivity enhancement due to technology transfer or R&D investment, which may take longer to materialise but have more sustainable effects on productivity than the compositional change[36].

The results from the use of the two different measures of productivity are also compared, one from the modified LP method and the other from the original method. Table 3.11 suggests that modifications lead to somewhat lower effects on productivity. The results in row (b) show that the coefficient in $s = 1$ is statistically significant in contrast to that in row (a). However, the results are quite similar. This finding can be regarded as a robustness check which confirms that offshoring has a significantly positive effect on productivity compared to their matched domestic firms at least during the first year of offshoring.

[36]The productivity enhancement from technology transfer or inputs of better quality can also be limited if offshoring is destined for low-income countries whose technology level is not higher or rather lower than that of the Korean manufacturing industry. Unfortunately, the data does not provide any information on the destination of offshoring.

Table 3.12: Offshoring and TFP (iv) - $\Delta\omega^{MOD}_{it+s}$

s	0	1	2
(a) Low			
$\beta_{DID-OFF}$	0.006	−0.041	−0.084
S.E.	(0.03)	(0.06)	(0.08)
T-stat	0.22	-0.61	-0.96
#. Treated	90	60	50
#. Non-Treated	4,530	2,977	2,321
(b) Medium-Low			
$\beta_{DID-OFF}$	−0.002	−0.044	−0.049
S.E.	(0.03)	(0.06)	(0.07)
T-stat	-0.07	-0.74	-0.68
#. Treated	77	50	43
#. Non-Treated	8,148	5,422	4,280
(c) Medium-High			
$\beta_{DID-OFF}$	0.087***	0.067*	0.107**
S.E.	(0.01)	(0.03)	(0.05)
T-stat	4.53	1.70	2.07
#. Treated	416	250	195
#. Non-Treated	18,388	12,126	9,399

Notes : Standard errors are reported in parentheses. * 10%, ** 5%, *** 1% level of significance.

3.7.3 Technology Intensity and Post-Entry Effects

The entire manufacturing industry can be divided into three different groups of industries depending on the level of technology intensity that is measured by the ratio of R&D expenditure to value-added. Table 3.12 indicates the effect of offshoring on the rate of productivity in three different groups of industries. The coefficients in rows (a) and (b) are neither positive nor statistically significant. This finding suggests that offshoring does not have productivity-enhancing impacts in the industries of low- and medium-low technology intensities.

However, the post-entry effect is highly significant in the industries of medium-high technology intensity. In $s = 0$, the coefficient is reported to be 8.7% and even significant under the 1% level. The coefficients remain positive and significant in later years, leading to 10.7%

Table 3.13: Offshoring and TFP (v) - Real TFP ω^R

s	0	1	2
$\beta_{DID-OFF}$	0.247***	0.116***	0.104***
S.E.	(0.01)	(0.01)	(0.01)
T-stat	18.35	7.35	6.14
#. Treated	583	360	288
#. Non-Treated	31,006	20,525	16,000

Notes : Standard errors are reported in parentheses. * 10%, ** 5%, *** 1% level of significance.

in the third year of offshoring. As offshoring often involves contracting out of low-skilled activities, which could have been carried out in-house, the composition/reallocation effect is expected to be relatively more conspicuous in the technology-intensive industries whose comparative advantage lies in high-skilled activities.

This finding has implications that, even though offshoring may have productivity-enhancing effects via composition effect or other channels, it does not uniformly apply to the whole manufacturing industry. The effect will be most conspicuous in industries with high technology intensity where the gap between the skill intensity in the offshored and non-offshored activities is expected to be most noticeable.

3.7.4 Real Total Factor Productivity

In Chapter 2, the distinction between total factor productivity and real total factor productivity (RTFP) was discussed. It also suggested the use of RTFP, as the measurement errors or temporary shocks can be removed, providing a clearer picture of a firm's efficiency. It was estimated using the following equation

$$RTFP_{it} = \hat{\omega}_{it} = \hat{\Phi}_t - \hat{\beta}_k k_{it} = \tilde{y}_{it} - \hat{\beta}_l l_{it} - \hat{\beta}_k k_{it} \tag{3.20}$$

where $\tilde{y}_{it}$ denotes predicted values from the estimation of equation (3.10). This differs from the usual TFP which is normally used in the existing literature (e.g. Olley and Pakes, 1996; Levinsohn and Petrin, 2003) as the latter includes the effects from transitory shocks, η_{it} as below

$$TFP_{it} = \widehat{\omega_{it} + \eta_{it}} = y_{it} - \hat{\beta}_l l_{it} - \hat{\beta}_k k_{it} \tag{3.21}$$

Table 3.14: Offshoring and TFP (vi) - Real TFP ω^R

s	0	1	2
(a) Low			
$\beta_{DID-OFF}$	0.266***	0.145***	0.184***
S.E.	(0.03)	(0.05)	(0.06)
T-stat	8.73	2.77	2.85
#. Treated	90	60	50
#. Non-Treated	4,530	2,977	2,321
(b) Medium-Low			
$\beta_{DID-OFF}$	0.223***	0.055	0.004
S.E.	(0.02)	(0.04)	(0.05)
T-stat	10.27	1.25	0.08
#. Treated	77	50	43
#. Non-Treated	8,148	5,422	4,280
(c) Medium-High			
$\beta_{DID-OFF}$	0.226***	0.117***	0.096***
S.E.	(0.01)	(0.02)	(0.02)
T-stat	25.32	4.98	3.26
#. Treated	416	250	195
#. Non-Treated	18,388	12,126	9,399

Notes : Standard errors are reported in parentheses. * 10%, ** 5%, *** 1% level of significance.

Table 3.13 shows the results of offshoring on productivity when productivity is measured by RTFP denoted by ω^R. Compared to the results in Table 3.11, the coefficient has become not only larger from 0.067 to 0.247 at $s = 0$ and they all become highly significant under 1% throughout $s = 0$ to $s = 2$. Table 3.14 also shows a marked difference in terms of magnitude as well as statistical significance, compared to those in Table 3.12. Overall, the positive impact has become stronger across the industries and remains significant for longer throughout the periods. As explained in the second chapter, RTFP is better at measuring the trend of productivity, as it is less disrupted by transitory shocks or measurement errors. Thus, the change in results indicates that the productivity-enhancing effect becomes more distinct when using RTFP, but less so when the conventional measure is employed.

3.8 Markups and Offshoring

Further to the second chapter, the relationship between offshoring and markups are examined in this section. The markups are estimated from the method suggested by De Loecker and Warzynski (2012). There are two possibilities that need to be taken into consideration, the first being that firms with higher markups are likely to self-select into offshoring. The second possibility is that firms that enter into offshoring benefit from the markup effect and experience an increase in markup.

3.8.1 Offshorer Premia

To examine the first possibility, firm-level markups are related to the firm's offshoring status as in the following regression framework

$$\ln \mu_{it} = \beta_0 + \beta_1 OS_{it} + \mathbf{X'}_{it}\gamma + \delta_j + \delta_t + \epsilon_{it} \tag{3.22}$$

where OS_{it} is an offshoring status dummy which denotes 1 if firm i offshores at time t and 0 otherwise. β_1 captures the percentage difference between firms that offshore and those that do not. $\mathbf{X}_{it}$ includes the usual control variables for markups. Industry (δ_j) and time (δ_t) fixed effects are included.

In addition, the level markup difference can also be estimated. To this end, De Loecker and Warzynski (2012) apply the percentage difference to the constant term which captures the non-offshoring firm's markup average. This level of markup difference is denoted as μ_{OFF} and is computed by $\mu_{OFF} = \beta_1 \exp(\beta_0)$.

Table 3.15 shows the results of a simple regression of firm-level markups on both OS_{it} using a fixed-effects model for the entire sample of firms. The results suggest the existence of markup premium. The mean percentage difference between offshorers and non-outsourcers is 14.5% when industry and time dummies are not included and 14.6% when included. They are both highly significant even under the 1% level of significance.

Table 3.15: Simple Regression of Firm-level Markups on Offshorer Status

	(1)	(2)	Obs
β_1	0.145^{***}	0.146^{***}	38,936
	(0.011)	(0.010)	
μ_{OFF}	0.059^{***}	0.073^{***}	38,936
	(0.005)	(0.008)	
Controls			
X	Yes	Yes	
Industry-Time	No	Yes	

Note: Standard errors are reported in parentheses. ***,** and * indicate significance at 1%, 5% and 10% respectively. The standard errors for μ_{OFF} are obtained from a non-linear combination of the estimated parameters.

The level of the markup difference is approximately 0.059 when industry and time dummies are not included and 0.073 when they are. Given the standard errors of a non-linear combination of the parameters, they are both highly significant even under the 1%. These results demonstrate that there is an evidence of the offshoring premium amongst the Korean manufacturers.

This is not so surprising a finding, as is one of the established empirical observations that offshoring firms are more productive compared to purely domestic firms (e.g Jabbour, 2010; Hijzen et al., 2010). Therefore, more productive firms are likely to have more capacity to charge higher markups compared to less productive counterparts.

3.8.2 Effect of Offshoring on Markups

Many empirical studies document that exporting or offshoring firms experience an increase in productivity (e.g. Bernard and Jensen, 1999; Hijzen et al., 2010). However, it can be also interesting to investigate whether markups are affected after a firm starts offshoring. This finding will enable a better interpretation of the almost unanimously positive productivity enhancement effect of either offshoring or exporting or both. To this end, offshoring firms are classified into three categories: starters, exiters and continuers[37].

$$\ln \mu_{it} = \gamma_0 + \gamma_1 START_{it} + \gamma_2 EXIT_{it} + \gamma_3 CONTINUE_{it} + \mathbf{X'}_{it}\sigma + \delta_j + \delta_t + \epsilon_{it} \tag{3.23}$$

[37] Starters are defined to be firms which did not engage in offshoring at least for two previous periods and start offshoring. Exiters are the firms which engaged in offshoring for at least two consecutive years and stop offshoring. Continuers are the ones which engage in offshoring throughout the sample period.

Table 3.16: Simple Regression of Firm-level Markups on Offshoring Decision

	(1)	(2)
γ_1	0.120^{***}	0.139^{***}
	(0.011)	(0.011)
μ_{START}	0.049^{***}	0.069^{***}
	(0.005)	(0.008)
γ_2	-0.063^{***}	-0.022^{***}
	(0.009)	(0.009)
γ_3	0.055^{***}	0.089^{***}
	(0.014)	(0.013)
Controls		
X	Yes	Yes
Industry-Time	No	Yes
Obs.	38,936	38,936

Note: Standard errors are reported in parentheses. ***,** and * indicate significance at 1%, 5% and 10% respectively. The standard errors for μ_{START} are obtained from a non-linear combination of the estimated parameters.

where $START_{it}$ denotes 1 if a firm i is a starter at time t and zero otherwise. In a similar vein, $EXIT_{it}$ ($CONTINUE_{it}$) denotes 1 if a firm i is an exiter (continuer) at time t and zero otherwise. γ_1 captures the percentage difference in markups before and after an offshoring decision. γ_2 captures the percentage difference when the firm i chooses to stop offshoring in t. $\mathbf{X}_{it}$ includes the control variables such as labour and capital use, which will represent the size and factor intensity. Industry (δ_j) and time (δ_t) fixed effects are also included.

The coefficient of main interest lies in γ_1. In a similar way, the level markup difference is defined as μ_{START} and computed by $\mu_{START} = \gamma_1 \exp(\gamma_0)$. Table 3.16 reports that the decision to start offshoring has a positive impact on higher markups. The first row shows that the coefficient is 0.120 in column (1) and 0.139 in (2), both being statistically significant under the 1%. This indicates that the decision to offshore is associated with about 12 to 13 % increase in markups. The second row reports the level markup differences, which are 0.049 and 0.069 in rows (1) and (2) respectively. These are also highly significant.

The empirical findings show that, as firms start offshoring, markups increase. This is an important observation as it helps to rethink the fact that the productivity is measured using sales variable rather than quantity. TFP thus created is therefore denoted as $TFPR$

(revenue-based TFP) whereas the quantity-based TFP is denoted $TFPQ$. This chapter looks at the link between a firm's decision to export and $TFPR$. It implies that a positive effect of exporting can be attributed to either of the two effects : improvement in technical efficiency or an increase in demand. The data availability does not allow to isolate one effect from the other, but, an intuition can be obtained from the following simple equation

$$TFPR_{it} = P_{it} TFPQ_{it} \tag{3.24}$$

where $TFPR$ is a product of $TFPQ$ and the firm level price P_{it}. Then, taking logs of (3.24) and transforming the variables into the growth form,

$$\Delta \ln P_{it} + \Delta \ln TFPQ_{it} = \Delta \ln TFPR_{it} \tag{3.25}$$

Rearranging for

$$\Delta \ln TFPQ_{it} = \Delta \ln TFPR_{it} - \Delta \ln P_{it} \tag{3.26}$$

Equation (3.26) suggests that the growth rate in $TFPQ$ consists of a growth rate in $TFPR$ plus a growth rate in firm-level prices, for the latter of which no data is available. The results in Table 3.16 only enable one to guess the magnitude of $\Delta \ln P_{it}$. If it is simply assumed that $\Delta \ln P_{it} \simeq \Delta \ln \mu_{it}$, then $TFPQ$ can be said to be smaller than the estimated $TFPR$ in this chapter. For example, it can be seen that there is a 24.7 % increase in real total factor productivity, whilst markups are found to increase by about 14.5%, making the change in TFP add up to 10.2%.

However, it is doubtful whether $\Delta \ln P_{it} \simeq \Delta \ln \mu_{it}$ would hold in the context of offshoring. With the current dataset, it is difficult to determine where to attribute the markup effect: prices or marginal costs. One may need firm-level information on prices to distinguish one from the other. However, offshoring differs from other international activities, such as exporting or importing, as it typically involves a substitution of foreign inputs, at cheaper prices. Thus, the markup effect from offshoring is likely to be associated with a reduction in marginal costs. Then, the resulting estimates for $TFPQ$ would become higher compared to the assumption of constant marginal costs. This investigation into markups provides an indirect way of confirming the positive effect of offshoring on productivity.

3.9 Conclusion

This chapter has attempted to answer the question of whether offshoring enhances productivity. There have already been many attempts to measure the effects of offshoring on productivity, but this chapter places more emphasis on the consistent estimation of production function coefficients, which has been given relatively little attention in the offshoring literature. The importance of consistent estimation of productivity cannot be more emphasised, especially when one focuses on the accurate evaluation of a firm's policy and its effects on productivity.

To this end, this chapter modified the Levinsohn-Petrin method (i) to control for selection bias in the spirit of Olley and Pakes (1996) and (ii) to include offshorer status in the estimation procedures as an additional state variable. These modifications are deemed necessary considering the facts that the Korean manufacturing industry has been dynamic in terms of entry and exits and that offshoring firms will face different market conditions relative to purely domestic counterparts. Moreover, an endogenous Markov process is assumed in the modified Levinsohn-Petrin method. De Loecker (2013) discusses the possibility of inconsistent estimation of the production function coefficients should an exogenous Markov process be incorrectly assumed. Most importantly, this chapter suggests using value-added as a dependent variable, in place of gross output, to avoid inconsistent estimation of capital in the second stage of the Levinsohn and Petrin method.

After obtaining the consistent estimates for productivity, the effects of offshoring on productivity are estimated using the DID-PSM method. It is established in the literature that firms with large employment, higher productivity, innovation, exporter status or under foreign ownership are likely to self-select into offshoring than those with lower productivity. To control for the self-selection bias, the instrumental variable method can be employed, however, it is generally difficult to find a valid instrumental variable. Thus, the DID-PSM method to control for selection bias on both observable and unobservable firm-level characteristics was employed in this chapter.

The positive correlation between offshoring and productivity begs the question whether it is the high productivity firms that self-select into offshoring firms or it is the offshoring firms which experience an increase in productivity after decision to offshore. In this chapter, evidence is provided in support of the self-selection hypothesis in line with the existing literature. It is also found that firms that start offshoring experienced a marked experience in productivity. The results show that offshoring starters experienced a change in productivity of 6.7 % at the first period of offshoring. However, the positive and significant effects were not found in later periods, suggesting the possibility of productivity enhancement through composition effect.

Moreover, it is found that these positive results become more significant and the magnitude becomes larger when productivity measure obtained from the original LP method is employed. The results show that offshoring starters experienced a change in productivity of 10.8% in the first year of offshoring and the significant effect persists up to the second year. This suggests that the modifications proposed in this chapter have brought in non-negligible changes in the results and, in some cases, have the possibility of delivering misleading results.

This chapter also accounts for the fact that productivity is measured using sales variable rather than quantity variable. The resulting productivity measure can increase not only due to technical efficiency but also to demand change. The current dataset is not sufficiently detailed to isolate one effect from the other. However, an alternative and indirect method is suggested in this chapter by investigating the link between markups and offshoring to measure the magnitude of the latter effect. The empirical finding shows a positive effect of offshoring on firm-level markups. This implies a possibility that part of the resulting productivity measured from sales data can be attributed to demand-side.

The conclusions that can be drawn from these observations are as follows. Firstly, offshoring has clear advantages for those firms intended to increase their productivity. Those engaging in offshoring are likely to experience an increase in productivity, at least during the first year of offshoring via composition effect. Secondly, the positive post-entry effect is not long-lasting, suggesting that long-lasting productivity enhancement through knowledge, technology transfer or investment in R&D does not materialise. Lastly, it needs to be emphasised that the choice of right measure of productivity is important. If the inconsistent estimator is incorrectly employed, then there is a possibility of a misleading evaluation of the firm's policy.

Appendix A

A.1 [Ch 1] Critique of Ackerberg et al. (2015)

Ackerberg et al. (2015) raise the identification issue with labour coefficient. A various data generating process (DGP) can be assumed for labour demand, but, analogous to m_{it} in Levinsohn and Petrin (2003), it is not unnatural to assume that it also depends on k_{it} and ω_{it} as below

$$l_{it} = s_t(k_{it}, \omega_{it}) \tag{A.1}$$

Then, $\omega_{it} = j_t(k_{it}, m_{it})$,

$$l_{it} = s_t(k_{it}, j_t(k_{it}, m_{it})) \tag{A.2}$$

which implies that the labour is a *deterministic* function of k_{it} and m_{it}. This leads to the identification issue of β_l in the first stage because l_{it} is perfectly collinear with $\Phi_t(k_{it}, m_{it})$. This implies that, once conditional on k_{it} and m_{it}, there is no variation left in l_{it} to identify β_l. In other words, labour at time t does not have any cross-sectional variability, making it impossible to identify β_l (Aguirregabiria, 2009).

Ackerberg et al. (2015) note that it would be least likely to observe perfect collinearity in practice in the sense that an estimate is actually produced in the first stage. They argue that the lack of perfect collinearity comes from misspecification, and not a consistent estimator of β_l (Ackerberg et al., 2007).

A.2 [Ch 1] Markups and Demand Elasticity

The firm i chooses the quantity q_i which maximises its profit as follows

$$\pi_i = p_i(q_i)q_i - TC_i(q_i) \tag{A.3}$$

where $p_i(\cdot)$ denotes the price set by the firm i and $TC_i(q_i)$ total cost function of firm i to produce q_i. Differentiating (A.3) with respect to q_i,

$$p_i^{'}(q_i)q_i + p_i(q_i) - MC_i = 0 \tag{A.4}$$

Solving for p_i,

$$p_i(\frac{p_i^{'}(q_i)q_i}{p_i} + 1) = MC \tag{A.5}$$

where $\frac{p_i^{'}(q_i)q_i}{p_i}$ refers to the reciprocal of the price elasticity of demand. It will be denoted as η. Then, (A.5) will be expressed as the following

$$p_i = \frac{1}{1+\eta}MC \tag{A.6}$$

If $\eta = 0$, then a firm i sets its price according to the level of marginal costs. This is the case of perfect competition in which firms do not have any market power to set their own prices. They are price-takers in the perfect competition. $\eta < 0$ implies that a firm becomes a price-setter. The lower η is, the lower the price elasticity of demand, the higher markups.

The firm's price elasticity of demand depends upon its successful differentiation from other products. If its products have lower substitutability due to its realised unique selling points, then the price elasticity will decrease, allowing it to set higher price over marginal costs. Such differentiation results from either product development, quality improvement or effective marketing, to the first two of which R&D can contribute.

A.3 [Ch 1] System GMM

The regression equation of consideration is as follows

$$y_{it} = +\beta_0 + \lambda y_{it-1} + \beta_1 x_{it} + \alpha_i + u_{it} \tag{A.7}$$

which is dynamic in nature because of the term y_{it-1}. The parameter of interest is β_1 and the long-run multiplier is $\frac{\beta_1}{1-\lambda}$. To get rid of the fixed effect α_i, (A.7) is differenced as follows

$$\Delta y_{it} = \lambda \Delta y_{it-1} + \beta_1 \Delta x_{it} + \Delta u_{it}, t = 3, \cdots T \tag{A.8}$$

for observations $t = 1, 2, \cdots, T$. Applying OLS to (A.8) produces inconsistent parameter estimates because Δu_{it} is correlated with Δy_{it-1}. For serially uncorrelated u_{it}, Δu_{it} is uncorrelated with $\Delta y_{i,t-k}$ for $k \geq 2$. This lays out a logical basis for the use of lagged variables as instruments.

Arellano and Bond (1991) regard the equation (A.8) as a system of $T-2$ equations, for each of which a different set of instruments is considered. For example, there are more lagged values which can be used as instruments in later periods. They argue for using lagged levels as the instruments for endogenous variables and the strictly exogenous regressors as the instruments of their own. However, it is pointed out that the lagged levels are poor instruments for first-differenced variables especially if the variables follow, or closely follow, a random walk (Arellano and Bover, 1995; Blundell and Bond, 1998). They, therefore, maintain the use of lagged levels as well as lagged differences as instruments. This expanded estimator is termed system GMM corresponding to the original estimator which is commonly called difference GMM.

There are a couple of issues to consider when system GMM estimator is employed. There are one-step and two-step system GMM, both of which produce consistent estimates, but the latter is asymptotically more efficient. However, unlike one-step GMM, the two-step GMM estimator produces downwardly biased standard errors. Thus, Windmeijer (2005)'s finite-sample correction is applied to control for such downward bias.

Moreover, even though this is not much problem for a short panel as the one used in this dissertation, if T is large, the system GMM produces too many instruments, which could result in poor performance. Therefore, the number of instruments, that is the maximum lag of an instruments, may need to be limited in some cases.

There are two necessary specification tests which need to pass for the GMM estimates to become valid. First, the system GMM requires that the errors are serially uncorrelated. If they are uncorrelated, Δu_{it} are correlated with Δu_{it-1}, but not with $\Delta u_{it-k}, k \geq 2$. Second, the Sargan or Hansen test needs to be performed to test over-identifying restrictions. The null hypothesis that the instruments are valid instruments is tested. The Sargan test is sensitive to the assumption of homoskedasitcity and no-serial correlation, thus the Hansen test is often used for the test. However, even the Hansen test can suffer from the problem of too many instruments, in which case implausible p-values of 1.000 could be generated (Roodman, 2009).

A.4 [Ch 1] Classification of manufacturing industries into categories based on R&D intensities

Low Technology
Food products and beverages
Textiles, wearing apparel and leather products
Wood and products of wood and cork
Paper and paper products
Furniture; other manufacturing
Medium-Low Technology
Coke and refined petroleum products
Rubber and plastic products
Other non-metallic mineral products
Basic metals
Fabricated metal products
Medium-High Technology
Chemicals and chemical products
Basic pharmaceutical products
Computer, electronic and optical products
Electrical equipment
Machinery and equipment n.e.c.
Motor vehicles, trailers and semi-trailers
Other transport equipment

Appendix B

B.1 [Ch 2] Olley-Pakes Method

This paper mainly employs the Levison-Petrin method. However, it should be noted that it basically builds upon the semi-parametric method suggested by Olley and Pakes (1996). Thus, this chapter briefly summarises their methods here. In estimating the firm-level production function, simply applying OLS can lead to biased estimators for the coefficients of input variables for two obvious reasons.

Firstly, it is likely to violate the assumption that explanatory variables are uncorrelated with the error term (endogeneity bias). The variables on the right hand side (variable inputs such as labour or intermediate inputs) can be correlated with the unobservable productivity shocks. It is because that 'unobservable' is only applied to the econometrician, but not to the firm. This can be expressed by decomposing ϵ_{it} into two parts, ω_{it} and η_{it}, as below

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + \omega_{it} + \eta_{it}$$

where the former is a part of the productivity observable to the firm and the latter is an i.i.d error term unknown to both firm and econometrician. The firm with this prior knowledge about ω_{it} will determine the level of inputs, making them no longer an exogenous variable. The resulting OLS coefficients are likely to be upwardly biased as they get to capture the effect of TFP on output.

Secondly, an endogenous decision of firms to enter or exit the market is likely to bias the coefficient of capital stock as the probability of survival depends on the level of capital stock. Firms with a high level of capital stock can survive a low level of productivity shock whilst those with a low level of capital stock is likely not to survive it and exit the market. This, unless properly accounted for, can cause a downward bias in the coefficient of capital as it may falsely lead us to conclude that firms with a high level of capital stock are not much more productive than those with a small level of capital stock (selection bias).

Olley and Pakes (1996) present a semiparametric method to circumvent these issues and obtain consistent estimators by using an investment (i_{it}) as a proxy variable to control for unobservable productivity shocks, ω_{it}. This is based on the assumption that an observable variable i_{it} carries an information on the unobservable ω_{it}. The OP method depends on several assumptions

(1) The current productivity, ω_{it}, depends on the previous period's productivity (a first-order Markov process)

(2) Investment depends on the state variable k_{it} and productivity ω_{it}, such that $i_{it} = i_t(k_{it}, \omega_{it})$

(3) Investment increases monotonically in ω_{it}, conditional on other state variables.

Building upon these assumptions, the OP method is conducted through three stages. In the first stage, the coefficients on variable inputs (labour and intermediate inputs) are estimated. Investment depends on the state variables such that $i_{it} = i_t(k_{it}, \omega_{it})$. The assumption (3) ensures that the investment function is invertible. Thus, it can be expressed as $\omega_{it} = i_t^{-1}(k_{it}, i_{it}) = h_t(k_{it}, i_{it})$. Then,

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + h_t(k_{it}, i_{it}) + \eta_{it} \tag{A.1}$$

Using $\phi_t(k_{it}, i_{it}) = \beta_0 + \beta_k k_{it} + h_t(k_{it}, i_{it})$,

$$y_{it} = \beta_l l_{it} + \beta_m m_{it} + \phi_t(k_{it}, i_{it}) + \eta_{it} \tag{A.2}$$

This regression can be estimated by approximating $\phi_t(k_{it}, i_{it})$ using some high-order polynomial in k_{it} and i_{it}. From this, a consistent estimate of the coefficients for variable inputs (labour or intermediate inputs) are obtained. However, the coefficient on capital cannot be isolated as $\frac{\partial y_{it}}{\partial k_{it}} = \beta_k + h_t^{'}(k_{it}, i_{it})$

In the second stage, the firm's survival is accounted for and, to this end, a survival indicator

χ_{it}, which takes on 1 if the firm's productivity ω_{it} exceeds a cut-off productivity ω^*_{it} and 0 otherwise, is employed. The output of a firm i in the next period $t+1$ is

$$y_{it+1} = \beta_0 + \beta_l l_{it+1} + \beta_k k_{it+1} + \beta_m m_{it+1} + \omega_{it+1} + \eta_{it+1} \tag{A.3}$$

Using $\omega_{it+1} = E[\omega_{it+1}|\omega_{it}, \chi_{it+1} = 1] + \zeta_{it+1}$ from assumption (1),

$$y_{it+1} = \beta_0 + \beta_l l_{it+1} + \beta_k k_{it+1} + \beta_m m_{it+1} + E[\omega_{it+1}|\omega_{it}, \chi_{it+1} = 1] + \zeta_{it+1} + \eta_{it+1} \tag{A.4}$$

Rearranging,

$$y_{it+1} - \beta_l l_{it+1} - \beta_k k_{it+1} = \beta_0 + \beta_m m_{it+1} + E[\omega_{it+1}|\omega_{it}, \chi_{it+1} = 1] + \zeta_{it+1} + \eta_{it+1} \tag{A.5}$$

Using $\theta(P_{it}, h_t) = \beta_0 + E[\omega_{it+1}|\omega_{it}, \chi_{it+1} = 1]$,

$$\begin{aligned} y_{it+1} - \beta_l l_{it+1} - \beta_k k_{it+1} &= \beta_m m_{it+1} + \theta(P_t, h_t) + \zeta_{it+1} + \eta_{it+1} \\ &= \beta_m m_{it+1} + \theta(P_t, \phi_t(k_{it}, i_{it}) - \beta_0 - \beta_k k_{it}) + \zeta_{it+1} + \eta_{it+1} \end{aligned} \tag{A.6}$$

where P_t represents the probability of survival at $t+1$, that is, $p(\omega_{it+1} > \omega^*_{it+1})$. This can be estimated using a probit regression. Also, $\phi_t = \beta_0 + \beta_k k_{it} + h_t$ is already estimated in the first stage.

In the third stage, the final regression

$$y_{it+1} - \hat{\beta}_l l_{it+1} - \hat{\beta}_m m_{it+1} = \beta_k k_{it+1} + \theta(\hat{P}_t, \hat{\phi}_t(k_{it}, i_{it}) - \beta_0 - \beta_k k_{it}) + \zeta_{it+1} + \eta_{it+1} \tag{A.7}$$

is estimated to obtain an estimate of the coefficient on capital. A non-linear least squares regression is applied to obtain $\hat{\beta_k}$.

B.2 [Ch 2] Average Treatment Effect on the Treated and Difference-in-Differences Propensity Score Matching Approach

The second chapter measures the impact of decision to export on productivity as measured by the average treatment effect on the treated (ATET). The outcome of the treated i is denoted as q_{1i}, whereas that of the non-treated i as q_{0i}. D_i is a dummy variable which denotes one if i receive the treatment and zero otherwise. Also, $\mathbf{X}$ is a vector of observable variables. Because it is impossible to directly measure the difference $q_{1i} - q_{0i}$, the comparison of the average outcomes of the treated and the non-treated is considered. However, the simple comparison would not provide a meaningful casual effect because of the selection bias as below

$$E[q_{1i}|D_i = 1] - E[q_{0i}|D_i = 0] = \underbrace{E[q_{1i}|D_i = 1] - E[q_{0i}|D_i = 1]}_{\text{ATET}} + \underbrace{E[q_{0i}|D_i = 1] - E[q_{0i}|D_i = 0]}_{\text{Selection Bias}} \tag{A.8}$$

To have a meaningful comparison, that is, to remove selection bias, Rosenbaum and Rubin (1983) suggest using the propensity score matching which assumes that the outcome q_{0i} is independent of treatment if a set of observable characteristics ($\mathbf{X}$) is controlled for. The assumption is as follows

$$q_{0i} \perp D_i | p(\mathbf{X}) \tag{A.9}$$

where $p(\mathbf{X})$ denotes the propensity score, the estimated probability of participating in exporting given a set of observable characteristics $\mathbf{X}$[1]. Rather than matching with respect to all observable and relevant characteristics, the propensity score matching (PSM) method matches export starters and non exporters based on the propensity score. Then, the ATET can be obtained by simply comparing the averages of outcome variables between them. If the assumption (A.9) holds, it follows that

[1]This is a weaker version of the conditional independence assumption.

$$q_{1i}, q_{0i} \perp D_i | p(\mathbf{X}) \tag{A.10}$$

which states that, if observed $\mathbf{X}$ are controlled for, the outcomes are independent of treatment. In other words, this implies, if individuals are with the same $\mathbf{X}$, that q_{0i} and q_{1i} and D_i are independent.

$$E[q_{1i}|D_i=1]-E[q_{0i}|D_i=0]=\underbrace{E[q_{1i}|D_i=1]-E[q_{0i}|D_i=1]}_{\text{ATET}} \tag{A.11}$$

where the selection bias disappears and the ATET remains. However, it is pointed out that **X** is a set of *observable* characteristics. Thus, if self-selection is based on unobservable characteristics, the assumption (A.9) cannot be guaranteed. This is the reason that the difference-in-differences (DID) method is employed. The effect of time-invariant unobservables can be removed by taking the difference in outcomes before and after the firm's decision to start exporting. Then, DID will control for time-invariant unobservable characteristics such as firm's production network, its preference towards risks or manager's motivation, which are not captured only by the inclusion of observable control variables. Then,

$$\begin{aligned} &E[\Delta q_{1i}|D_i=1]-E[\Delta q_{0i}|D_i=0] \\ &\quad=\underbrace{E[\Delta q_{1i}|D_i=1]-E[\Delta q_{0i}|D_i=1]}_{\text{ATET}}+\underbrace{E[\Delta q_{0i}|D_i=1]-E[\Delta q_{0i}|D_i=0]}_{\text{Selection Bias}} \end{aligned} \tag{A.12}$$

The selection bias in (A.12) can be removed by the following assumption corresponding to (A.9)

$$\Delta q_{0i} \perp D_i | p(\mathbf{X}) \tag{A.13}$$

B.3 [Ch 2] Procedures for PSM

To construct a valid control group, a propensity score matching approach is employed. The propensity score matching allows pairing of each exporting starter with a similar firm that has never exported. This similarity is measured in terms of the likelihood of a firm starting to offshore based on their pre-offshoring observed characteristics **X**.

Procedures are intuitive. Firstly, the predicted probability of a firm's decision to export at time t (the propensity score) is estimated conditional on a vector of observed variables **X** using the following a random-effects probit model

$$Pr(START_{it}=1)=\Phi(h(\mathbf{X}_{it-1}),\delta_j,\delta_t) \tag{A.14}$$

where $\Phi(\cdot)$ denote the cumulative normal distribution and $\mathbf{X}_{it-1}$ denote a set of control variables of a firm i at $t-1$. $h(\mathbf{X}_{it-1})$ is a function of observed variables with linear and higher order terms. The choice of which higher order terms to include is based on the need to satisfy the balancing hypothesis more in detail later (Becker and Ichino, 2002). The estimation of (A.14) starts with a parsimonious probit specification.

The probability is estimated as a function of capital, TFP, foreign ownership and the number of employees in the previous period, which are known to have an impact on a firm's decision to export[2]. Among these, the inclusion of productivity is foremost important, because it controls for the fact that more productive firms are more likely to self-select into the international market. Differences in productivity will be conditioned on these pre-exporting observed variables, thereby reducing self-selection bias. This chapter also includes a full set of time (δ_t) and industry (δ_j) dummies to control for shocks common to all firms.

Secondly, once the propensity scores are estimated, the next step is to ensure that propensity scores are balanced between the treated and control groups. In other words, the propensity score should have a similar distribution between the two groups. The propensity score's distribution in each group is roughly estimated by splitting the sample by k equidistant intervals of the propensity score and test whether the average propensity score of the treated and the control groups is the same in all k intervals. If it is not equivalent, one or more intervals can be split into smaller blocks until equality holds in all the intervals.

Thirdly, a t-test is performed to check the mean equality for each characteristics within each interval. This is the balancing hypothesis test, first introduced by Rosenbaum and Rubin (1983) and formalised by (Becker and Ichino, 2002). If the hypothesis is rejected, then a different specification of $h(\mathbf{X}_{it-1})$ can be considered. The balancing hypothesis ensures that two observations with the same propensity score are similar in terms of observed variables $\mathbf{X}$, independently of the treatment[3].

Lastly, given the aforementioned hypotheses are all met, the PSM method matches the outcome of each exporting starter with the weighted outcome of non-exporters in the control

[2]If the sample size is sufficiently large, it is beneficial to include all variables that are thought to be potentially associated with the outcome, but not the treatment because there is a possibility that they are also correlated with the treatment. However, with the small sample size, variables with weak association with the outcome are better to be excluded because they can introduce too much noise in treatment effect and obscure any reduction in bias (Garrido et al., 2014). The variables included in the probit estimation are highly associated with the firm's outcome as well as the treatment.

[3]Exact balance is not easy to achieve. 10 to 25 % are proposed as maximum standardised differences for specific variables (Austin, 2009). It is more crucial to achieve balance in variables theoretically more important than those less likely to affect the outcome (Garrido et al., 2014).

group. There are many available matching techniques such as nearest neighbour matching (N-N), kernel or radius matching. The most commonly used matching is the N-N matching in which an observation with the propensity score p_i in the treated group is matched with the other observation in the control group with the propensity score p_j closest to p_i. However, this method can perform poorly, because the nearest neighbour has a propensity score which is widely different. Moreover, if there are many similar neighbours with reasonably close propensity scores, the N-N matching discards them only because they are not the closest.

B.4 [Ch 2] Korean Standard Industrial Classification (KSIC)

No.	Code	Name of Industry
1	10	Food Products
2	11	Beverages
3	12	Tobacco Products
4	13	Textiles
5	14	Wearing Apparel
6	15	Leather and Related Products
7	16	Wood and Products of Wood and Cork, Except Furniture
8	17	Paper and Paper Products
9	18	Printing and Reproduction of Recorded Media
10	19	Coke and Refined Petroleum Products
11	20	Chemicals and Chemical Products
12	21	Basic Pharmaceutical Products and Pharmaceutical Preparations
13	22	Rubber and Plastics Products
14	23	Other Non-Metallic Mineral Products
15	24	Basic Metals
16	25	Fabricated Metal Products, Except Machinery and Equipment
17	26	Computer, Electronic and Optical Products
18	27	Electrical Equipment
19	28	Machinery and Equipment N.E.C.
20	29	Motor Vehicles, Trailers and Semi-Trailers
21	30	Other Transport Equipment
22	31	Furniture
23	32	Other Manufacturing
24	33	Repair and Installation of Machinery and Equipment

Appendix C

C.1 [Ch 3] Summary of the Existing Literature

	Country	Data Level	Period	Productivity Effects		
				Material	Services	*M/S*
Wagner (2011)	Germany	Firm	2001-2003			+
Görg and Hanley (2005)	Ireland	Plant	1990-1995	+	*ns*	
Schwörer (2013)	European Countries	Firm	1995-2008	+	+	
Görg et al. (2008)	Ireland	Plant	1990-1998	*ns*	+	
Hijzen et al. (2010)	Japan	Firm	1994-2000			+
Jabbour (2010)	France	Firm	1990-2001			+
McCann (2011)	Ireland	Firm	2001-2005			+

M/S indicates offshoring intensity in which material offshoring is not distinguished from service offshoring. *ns* indicates that the effects are *not significant*.

C.2 [Ch 3] Measurement of Offshoring Intensity

To estimate the effects of offshoring on productivity, it is necessary to measure the intensity of offshoring. When industry-level offshoring intensity is considered, the main source of data is usually an input-output table and there is a well-established method to construct offshoring intensity indices. The firm-level measures of offshoring intensity are similar to industry-level counterparts in their form, but differ in that they are built based on the firm-level survey data. As there is no unification of survey questions across countries (or even within the same country), the resulting measures cannot help but differ from one another, depending on the data availability. Its most basic form is as below

$$OINT_{it} = \frac{IM_{it}}{Y_{it}} \tag{A.1}$$

where IM_{it} is real imported inputs and Y_{it} is real output for firm i at time t. It may look overly simple to construct at first glance, but a couple of clarifications needs to be mentioned on both IM_{it} and Y_{it}. Firstly, it should be made clear as to the range of IM_{it}. If it denotes inputs imported in the process of contracting out in-house activities to foreign vendors, the index measures 'narrow' offshoring intensity. On the other hand, if it simply denotes any imported inputs, the index measures 'broad' offshoring intensity. As Feenstra (1998) note, a narrow offshoring index is more appropriate in that it is consistent with the original concept of offshoring where activities are contracted out to foreign vendors, when they could have been done in-house. However, as briefly mentioned above, such distinction is often subject to availability and detail of data.

Secondly, it is worth noting that offshoring is defined as the ratio of imported intermediate inputs to output as in Geishecker and Görg (2008). This is different from other variables often used for normalisation such as non-energy total inputs (Feenstra, 1998; Amiti and Wei, 2009), total wage (Girma and Gorg, 2004), and value-added (Hijzen et al., 2010). However, following Geishecker and Görg (2008) and Schwörer (2013), this chapter uses output in the denominator. They point out that using the aforementioned variables - value-added and total inputs - can be misleading as increasing domestic outsourcing, which will decrease value-added and increase total inputs, leads to a change in offshoring intensity with no real change in it.

C.3 [Ch 3] Selection Bias in Olley-Pakes Model

Firms do exit and enter over period. This process of firm dynamics will be conspicuous especially if the sample period of interest is not trivial. The ongoing exit and entry of firms have been dealt with by omitting all firms that enter or exit over the sample period and constructing a balanced panel dataset (Van Beveren, 2012). However, this can result in a biased coefficient, because firms with low productivity have a stronger tendency to exit than those with high productivity. The Olley-Pakes directly controls for this selection bias by relying on the fact that firms with a higher level of capital are likely to withstand lower realisation of productivity. Each firm is assumed to follow the following exit rule

$$\chi_{it} = \begin{cases} 1 & \text{if } \omega_{it} \geq \underline{\omega}_t(k_{it}) \\ 0 & \text{if } \text{ otherwise} \end{cases} \tag{A.2}$$

where $\underline{\omega}_t(k_{it})$ represent a cut-off productivity, which in turn is a function of capital level. If a firm's realised productivity is below the cut-off productivity, they will choose to exit the market. Given that the productivity follows

$$\omega_{it} = E[\omega_{it}|\omega_{it-1}, \chi_{it} = 1] + \zeta_{it} \tag{A.3}$$

where the first term of (A.3) denotes that the expected value of productivity is conditional on the firm's survival. For simplicity, consider the following regression equation

$$y_{it} = \beta_k k_{it} + \beta_l l_{it} + \omega_{it} + \eta_{it} \tag{A.4}$$

where the all the notations are the same as in the previous chapters. Substituting (A.3) into (A.4),

$$y_{it} = \beta_k k_{it} + \beta_l l_{it} + E[\omega_{it}|\omega_{it-1}, \chi_{it} = 1] + \zeta_{it} + \eta_{it} \tag{A.5}$$

from which the omission of $E[\omega_{it}|\omega_{it-1}]$ can result in omitted variable bias. This is because the survival of firms with low productivity is correlated with the level of capital stock, hence the low level of cut-off productivity.

C.4 [Ch 3] Industry-level Production Function Estimation Results, using extended Levinsohn-Petrin Method

	β_l		β_k	
Industry	OLS	LPMOD	OLS	LPMOD
13	0.926	0.630***	0.166	0.121***
		(0.026)		(0.024)
14	0.813	0.539***	0.216	0.133***
		(0.026)		(0.026)
17	0.831	0.477***	0.342	0.039
		(0.029)		(0.043)
20	0.803	0.576***	0.365	0.283***
		(0.020)		(0.022)
22	0.839	0.645***	0.249	0.244***
		(0.019)		(0.028)
23	0.698	0.467***	0.371	0.065
		(0.021)		(0.047)
24	0.888	0.795***	0.260	0.065
		(0.019)		(0.046)
25	0.860	0.674***	0.268	0.113***
		(0.017)		(0.034)
26	0.896	0.621***	0.201	0.281***
		(0.017)		(0.022)
27	0.871	0.616***	0.210	0.188***
		(0.025)		(0.028)
28	0.973	0.772***	0.186	0.099***
		(0.020)		(0.026)
29	0.905	0.634***	0.220	0.095***
		(0.014)		(0.024)
30	0.796	0.554***	0.313	0.115***
		(0.013)		(0.022)
31	0.794	0.463***	0.305	0.135***
		(0.035)		(0.062)
32	0.765	0.463***	0.309	0.218***
		(0.061)		(0.058)
33	0.892	0.604***	0.220	0.099**
		(0.048)		(0.051)

***,** and * indicate significance at 1%, 5% and 10% respectively.

C.5 [Ch 3] Production Function Coefficients Between LP methods with Exogenous and Endogenous Markov Process

		β_k	
Industry	LPEXT	LPMOD	**Diff.**
13	0.119	0.121	1.68%
14	0.136	0.133	-2.20%
17	0.038	0.039	2.63%
20	0.284	0.283	-0.35%
22	0.245	0.244	-0.40%
23	0.075	0.065	-13.33%
24	0.068	0.065	-4.41%
25	0.105	0.113	7.61%
26	0.313	0.281	-10.22%
27	0.186	0.188	1.07%
28	0.097	0.099	2.06%
29	0.094	0.095	1.06%
30	0.118	0.115	-2.54%
31	0.146	0.135	-7.53%
32	0.215	0.218	1.39%
33	0.110	0.099	-1.10%

C.6 [Ch 3] Industry-level Total Factor Productivity (TFP) Estimation, using extended Levinsohn-Petrin Method

Code	Mean (Overall)	S.D. (Overall)	S.D. (Between)	S.D. (Within)	Obs.	Group	$\bar{T}$
13	5.253	0.546	0.594	0.216	1874	353	5.30
14	6.526	0.887	0.869	0.283	1498	285	5.25
17	7.273	0.802	0.773	0.189	1105	186	5.94
20	4.518	0.727	0.674	0.317	2877	521	5.52
22	4.204	0.516	0.477	0.272	3118	621	5.02
23	7.114	0.834	0.797	0.240	1519	287	5.29
24	5.562	0.635	0.583	0.314	2705	501	5.39
25	5.444	0.622	0.614	0.247	2712	640	4.23
26	3.871	0.749	0.759	0.394	5853	1313	4.45
27	4.841	0.555	0.531	0.274	1535	331	4.63
28	4.940	0.628	0.584	0.332	2747	596	4.60
29	5.825	0.630	0.629	0.295	5259	1093	4.81
30	6.008	0.659	0.643	0.262	5768	1046	5.51
31	6.580	0.992	0.940	0.327	922	216	4.26
32	5.498	0.648	0.599	0.264	418	89	4.69
33	5.565	0.712	0.761	0.241	463	108	4.28

$\bar{T}$ is the average number of periods for which the panel is observed. Not being an integer, $\bar{T}$ indicates that the panel is unbalanced.

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